Traffic Sign Classification Using Ring Partitioned Method

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***Abstract*---Traffic sign recognition usually consists of two parts : detection and classification. In this paper we describe the classification stage using ring partitioned method. In this method, first the RGB image is converted into gray scale image using color thresholding and histogram specification technique. This gray scale image, called as specified gray scale image is invariant to the illumination changes. Then the image is classified using ring partitioned method. The image is divided by several concentric areas like rings. In every ring the histogram is used as an image descriptor. The matching process is done by computing the histogram distances for all rings of the images by introducing the weights for every ring. The method doesn't need a lot of samples of sign images for training process, alternatively only the standard sign images are used as the reference images. The experimental results show the effectiveness of the method in the matching of occluded, rotated, and illumination problems of traffic sign images**.

I. INTRODUCTION

Road traffic signs are important parts in the transportation system. An intelligent system for recognizing traffic signs would be benefical in several ways. It could assist the driver before passing them; a warning system sends signal to the driver as response to the traffic sign, for example the speed limitation.The driver assist system will make the driving more safer and easier. In the autonomous vehicle, in which no human driver in the car, the traffic sign recognition become essensial part in order to guide the vehicle when running in the street. The maintenance and inventory of those signs are the other benefits. By recognition of the status or condition about the traffic signs, the maintenance and inventory can be effectively done using intelligent vision system rather than manual inspection by human.

Researchers divide the traffic sign recognition system into two stages : the detection stage and the classification stage [1,3,4,5,7]. In the detection stage, color or shape features are used to generate the candidate regions where traffic signs might exist in a particular image. In the classification stage, the candidate signs obtained before are classified. There are no standard algorithm in the both stages. Neural networks are used in the classification stage in [3,4,7]. In [5], the technique of Markov model is used to classify the sign. The matching pursuit filter is used for classification in [1].

The above-mentioned methods consider the rotated, scaled, illumination changes of the traffic sign images. In [3,4,7] the rotated, scaled, and imperfect signs were used as training patterns of artificial neural networks. Those signs were also used as training patterns of matching pursuit filter in [1]. In [1], since matching pursuit filter uses wavelet to extract the features, the recognition is invariant to the illumination changes. In [7], the lighting, weather, and shadows influences are reduced by converting the original image to the new image using a pre-selected formula. After conversion, only pixels whose original red components dominate the other two components (green and blue) can have a nonzero red component in the new image. The hue and saturation components were taking into account in order to avoid lighting condition [3]. In [4], the template based correlation which was immune to the lighting changes was used.

The partial occluded images were considered in [3,7]. In [3] the occlusion affects the hue values, producing the high variance. In the classification stage, the occlusion information obtained in the first analysis is used to decide the matching image given by neural network. If the network discovers that there is no learnt pattern similar enough to the sign presented, the system verifies if there is occlusion. In the case of occlusion, the maximum value is taken although it was low. On the other hand, if the network response is high but there is an occlusion, it means that the occlusion is small and affects only the sign border. In [7], the partial occluded signs were used in the training process by added Gausssian noise and shift the perfect signs to the left, right, up and down.

In the previous works, artificial neural network or matching filter are used to classify the traffic signs. Those methods need a lot of samples of signs in the training process to achieve a good recognition of the disturbed signs. Concerning with the occlusion problem, in [7] the result depends on the sample patterns used in the training process. Meanwhile, in [3] the occlusion information obtained in the previous analysis is used to justify the classification of the neural network. Here, we propose a new simple method to cope with the problems of occlusion, rotation, and illumination changes of traffic sign images. The method doesn't need a lot of samples of sign images for training process, alternatively only the standard sign images are used as the reference images. In order to cope with the occlusion problem, we take into account the degree of occlusion in the matching process. It will increase the robustness of the matching regarding to the occlusion. The method divides a rectangular image into several rings, called as ring partitioned method. An additional method is introduced in the pre-processing stage to convert the RGB image into a gray scale image which is invariant to illumination changes, called as specified gray scale image. The histogram distance matching is used to match the target images with the reference images. Since, the histogram is used, the rotation invariant properties is acquired. Comparing with the others, the proposed method is simple, fast, and robust.

The outline of the paper is as follow. In section 2, we introduce the pre-processing stage to convert RGB image into a specified gray scale image. The ring partitioned matching method is explained in section 3. Section 4 contains the experimental results. Conclusion is covered in section 5.

II. PRE-PROCESSING

The traffic sign images often come with unperfect images. The signs are partially occluded by objects or interfered by shadows, rotation, oblique (image that taken from side view) and affected by illumination changes. Since the illumination changes influence the histogram of image, a pre-processing stage is needed to convert a RGB image into a gray scale image which is invariant to the illumination changes and shadows. Here, we propose a simple method based on color thresholding to convert a RGB image into a gray scale image. Fig. 1 illustrates the proposed method.

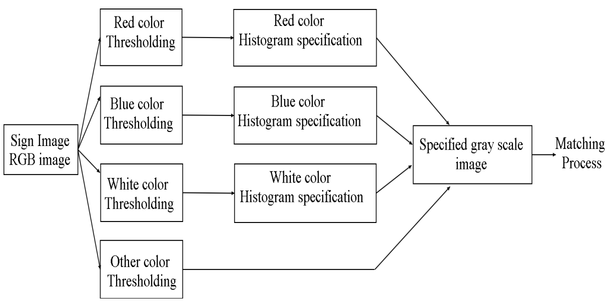


Figure 1. Pre-processing.

The traffic signs used in the experiment are limited to the circular sign with red color border (include the no entry sign). Using this limitation, there are three kinds of colors in the signs, i.e. red, blue, and white. The color thresholding then applied to the RGB image to extract the red, blue, white, and other colors of the image. After color thresholding, the gray scale image for each color can be obtained. Since an image is segmented by four color thresholding, there are four gray scale images corresponding to each color. Using histogram specification technique [11], we can create an image with a particular histogram. By selecting the different gray scale ranges in each image, finally we can combine four images into an image where gray scales range for red, blue, white, and other colors(black color) are definitely separated.

Another problem in the real sign image is the occlusion. The sign often occluded by other object such as trees, poles, leaves, etc. Most of the occlusions are caused by trees and poles. The trees appear with the brown or green color. In this case, the color thresholding is able to classify the trees as black object properly, likewise the dark or black poles. However, the white or gray poles can not be solved by the color thresholding. Since they are similar to the white color, they will have the same appearance with the white color of the sign. Here, we assume that the white pole which occlude the sign image is straight pole and cover the image sign from upper side until lower side of the circle. By this assumption, the white pole can be separated from white color in the sign background using the information from the red circle of the image. Shortly, if a pole occludes the sign image, the red color in some columns of the image will be missed. If it occurs, the pixels along those columns are replaced with the black color. To examine the columns of image which is occluded, the projection technique [5] of red color is employed.

The sign mages come with the different sizes. The specified gray scale image obtained before is resized to the size 70x70 pixels. The resizing image is used to speed up the matching process. Beside that, by resizing the image into a square image, an oblique image which the circular red sign appears as an ellipse can be converted into a circle.

III. RING PARTITIONED MATCHING

A. Basic idea

Histogram is a simple descriptor for an image. Since, the histogram only counts the number of pixels for each gray scale (or color) value, the spatial information is lost. Some different images will have the same histograms, such as shown in fig. 2. Suppose there are two black and white images *A* and *B*, if we divide the images into four areas as shown in fig. 3, the above problem can be reduced.

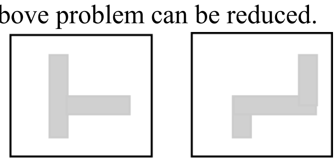


Figure 2. Two different images with the same histogram.

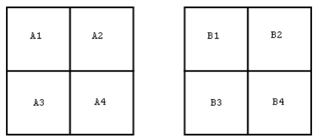


Image *A* Image *B*

Figure 3. Image partition.

Let h_A and h_B are histograms of image *A* and *B*, respectively. $h_{A1}, h_{A2}, h_{A3}, h_{A4}, h_{B1}, h_{B2}, h_{B3}, h_{B4}$ are histograms of sub-images $A_1, A_2, A_3, A_4, B_1, B_2, B_3, B_4$, respectively. Suppose that,

$$\begin{aligned}
&h_{A1}(0) = p; h_{A1}(1) = m - p; h_{A2}(0) = q; h_{A2}(1) = m - q;\\
&h_{A3}(0) = r; h_{A3}(1) = m - r; h_{A4}(0) = s; h_{A4}(1) = m - s;\\
&h_{B1}(0) = q; h_{B1}(1) = m - q; h_{B2}(0) = p; h_{B2}(1) = m - p;\\
&h_{B3}(0) = r; h_{B3}(1) = m - r; h_{B4}(0) = s; h_{B4}(1) = m - s;
\end{aligned} \tag{1}$$

where,

$h_*(0) =$ number of black pixels,

$h_*(1) =$ number of white pixels,

$m =$ total pixels in a sub - image,

p, q, r, s : positive integers.

Then, the histograms of image *A* and *B* are :

$$\begin{aligned}
&h_A(0) = p + q + r + s; h_A(1) = 4m - (p + q + r + s)\\
&h_B(0) = q + p + r + s; h_B(1) = 4m - (q + p + r + s)
\end{aligned} \tag{2}$$

The distance between *A* and *B* ($dist\_AB$) can be computed using the Euclidean's distance. In general, the distance between *A* and *B* in Euclidean space R^n is given by

$$dist\_AB = |A - B| = \sqrt{\sum_{i=1}^{n} (A_i - B_i)^2} . \tag{3}$$

In the case of (1), this distance is given by

$$dist\_AB = \sqrt{\sum_{i=1}^{4}(h_{Ai}(0)-h_{Bi}(0))^2 + \sum_{i=1}^{4}(h_{Ai}(1)-h_{Bi}(1))^2} \,. \quad (4)$$

In the case of (2), this distance is given by

$$dist\_AB = \sqrt{(h_A(0)-h_B(0))^2 + (h_A(1)-h_B(1))^2} \,. \quad (5)$$

If we compute the distance between A and B ($dist\_AB$) using sub-images such as in (1), then from (1) and (4) we obtain

$$dist\_AB = \sqrt{2(p-q)^2 + 2(p-q)^2} = 2|(p-q)| \,. \quad (6)$$

Meanwhile, if we compute the histogram distance between A and B ($dist\_AB$) using (2), then from (2) and (5) we obtain

$$dist\_AB = 0 \,. \quad (7)$$

From (6) and (7) (with assumption that $p \neq q$), we obtain that two different images with the same histograms can be recognized as two different images if we make partition of the image and compute the histogram distance based on the partition.

The above idea can be extended to solve the occlusion problem. In the fig. 4, image A is an image without occlusion, image B is the another image, and image C is image A with occlusion. Human can intepret easily that image C is more similar to A than B. Here, we will show that the partition method shows better performance than non-partition method to interpret the occluded image C.

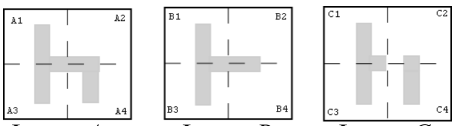


Image A (a) Image B (b) Image C (c)

Figure 4. Image partition in the occluded image.

Let images in fig. 4 be partitioned into four areas in the same way as fig. 3. By inspecting the pictures, we have

$$\begin{aligned} &h_{A1}(0)=p\,;h_{A2}(0)=q\,;h_{A3}(0)=r\,;h_{A4}(0)=s;\\ &h_{B1}(0)=p\,;h_{B2}(0)=q\,;h_{B3}(0)=r\,;h_{B4}(0)=s-\beta;\\ &h_{C1}(0)=p\,;h_{C2}(0)=q-\alpha\,;h_{C3}(0)=r\,;h_{C4}(0)=s-\alpha; \end{aligned} \quad (8)$$

where $\beta = 4\alpha$; p,q,r,s,α,β : positive integers.

The distance between image A and C (*dist_AC_P*) and distance between image B and C (*dist_BC_P*) for partitioned images are obtained as

$$dist\_AC\_P = 2\alpha \,, \quad (9)$$

$$dist\_BC\_P = 2\alpha\sqrt{5} \,. \quad (10)$$

If the distances are calculated for non-partitioned images, the results are given as

$$dist\_AC\_NP = 2\alpha\sqrt{2} \,, \quad (11)$$

$$dist\_BC\_NP = 2\alpha\sqrt{2} \,. \quad (12)$$

From (9)-(12), if we compute the distance of image without partition, the distance between image A and C is the same as the distance between B and C, or image C (image A with a partial occlusion) can be recognized as image A or as image B. However, using partition method, the distance between image A and C is lower than the distance between image B and C, thus image C is more similar to image A than to image B, similarly to the human interpretation.

Let us observe the general case to make the partitioning effects clear. We can discuss it with two partitions without any loss of generality. Let A and B are the reference images and C is a target image. The target image C is an occluded image of A. Suppose that

$$\begin{aligned} &h_{A1}(0)=p; h_{A2}(0)=q;\\ &h_{B1}(0)=p+\beta_1; h_{B2}(0)=q+\beta_2;\\ &h_{C1}(0)=p-\gamma_1; h_{C2}(0)=q-\gamma_2; \end{aligned} \quad (13)$$

where

$0 \le p \le m; 0 \le q \le n; -p \le \beta_1 \le m-p; -q \le \beta_2 \le n-q;$

$0 < \gamma_1 \le p; 0 < \gamma_2 \le q;$

m: number of pixels of the 1st partition;
n: number of pixels of the 2nd partition.

The distances between A and C and between B and C for partitioned images are obtained as

$$dist\_AC\_P = \sqrt{2(\gamma_1^{\,2} + \gamma_2^{\,2})} \,, \quad (14)$$

$$dist\_BC\_P = \sqrt{2(\beta_1+\gamma_1)^2 + 2(\beta_2+\gamma_2)^2} \,. \quad (15)$$

For non-partitioned images, the distances are obtained as

$$dist\_AC\_NP = \sqrt{2(\gamma_1+\gamma_2)^2} \,, \quad (16)$$

$$dist\_BC\_NP = \sqrt{2(\beta_1+\beta_2+\gamma_1+\gamma_2)^2} \,. \quad (17)$$

In the partitioned case, C is more similar to A than B, if the next condition is satisfied.

$$(\beta_1+\gamma_1)^2 + (\beta_2+\gamma_2)^2 > \gamma_1^{\,2} + \gamma_2^{\,2} \,. \quad (18)$$

In the non-partitioned case, the condition is

$$(\beta_1+\beta_2+\gamma_1+\gamma_2)^2 > (\gamma_1+\gamma_2)^2 \,. \quad (19)$$

or

$$(\beta_1+\gamma_1)^2 + (\beta_2+\gamma_2)^2 > \gamma_1^{\,2} + \gamma_2^{\,2} + 2\gamma_1\gamma_2 - 2(\beta_1+\gamma_1)(\beta_2+\gamma_2). \quad (20)$$

If β_1 and β_2 are positive, the inequalities in (18) and (19) are always satisfied. It means that by using partitioned or non-partitioned method, we can classify image C as the original image A properly.

In the case where β_1 and β_2 are negative or have the different signs, there is no guarantee that (18) and (19) are satisfied. However, (18) is always satisfied when (19) holds, if the next condition is satisfied.

$$\gamma_1\gamma_2 - (\beta_1+\gamma_1)(\beta_2+\gamma_2) > 0 \,. \quad (21)$$

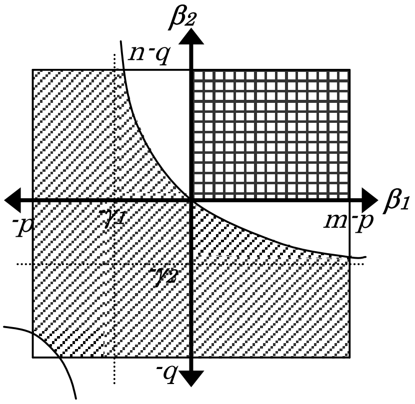
Namely if the above inequality holds, the partitioned case shows the better performance than the non-partitioned case.

Let us examine the case where (21) holds. From (21), we get the following inequality (it is assumed that $\beta_1 \neq 0$ and $\beta_2 \neq 0$, for convenience).

$$\beta_2 < -\frac{\beta_1\gamma_2}{\beta_1+\gamma_1} \text{ if } \beta_1 > -\gamma_1;\ \beta_2 > -\frac{\beta_1\gamma_2}{\beta_1+\gamma_1} \text{ if } \beta_1 < -\gamma_1. \tag{22}$$

In the case of $\beta_1 = -\gamma_1$, (21) always holds. For given occlusion, namely γ_1 and γ_2, the combinations of β_1 and β_2 satisfying (22) are shown in fig. 5.

As shown in fig. 5, the area where (22) is satisfied is larger than the area where (22) is not satisfied, if the occlusion (γ_1, γ_2) is not so large compared with (p,q) of the original image. Thus the partitioned case shows the better performance than the non-partitioned case in many cases.



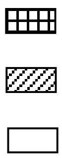


Figure 5. Solution areas of (22).

The effect of the partitioning will increase by partitioning the image into more than two areas. Here, we use the ring (circle) partition, where an image is partitioned into several areas like rings. An image is partitioned into k-rings with the same space/width as shown in fig. 6. The ring is numbered from the innermost ring. The outermost ring actually doesn't form a ring. Since an image is rectangular, the outermost ring is used to make a complete partition of an image.

Comparing with square partition such as in fig. 3, the ring partition has the following advantages :

- Since an image is partitioned into ring areas, it is invariant to the rotation.
- Since the traffic sign images are circular signs, the inner parts of the ring partitions have more important information than the outer parts. Thus using ring partition, we can adjust the weighting factors easier rather than square partition.

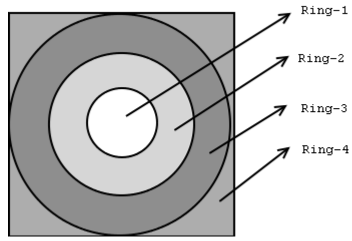


Figure 6. Ring partition.

B. Fuzzy histogram

The histogram provides the information about the dynamic range of gray distribution in an image. The gray value n in a digital image can be $(n+1)$ or $(n-1)$ without any appreciable change in the visual perception. Such imprecisions are not considered in the normal/usual histogram. The fuzzy histogram considers the uncertainty arising out of the imprecision of gray levels of the image.

The fuzzy histogram is expressed as [10] :

$$fh(k) = \sum_{k' \in \mu} h(k')\mu_k(k') \tag{23}$$

where $h(k')$ is usual normalized histogram.

$\mu_k(k')$ is the resemblance degree of gray level k' to the gray level k.

In the case of symmetrical triangular membership function, $\mu_k(k')$ is expressed :

$$\mu_k(k') = \max\left(0, 1 - \frac{|k'-k|}{\alpha}\right) \tag{24}$$

α *is a positive real number.*

A fuzzy histogram provides a smoothed histogram. By smoothing the histogram, such imprecisions of image caused by the natural of image or along the digital image processing can be reduced. Since in the digital image we work with the discrete level, the specified histogram obtained by the histogram specification technique is not exactly similar to the particular histogram. The fuzzy histogram makes the specified histogram similar to this particular histogram.

C. Matching strategy

Matching between target image and reference images basically finds the reference image which has the highest similarity with the target image or the lowest distance to the target image. The distance or similarity is computed from the the extracted features of image called image descriptor. The histogram is used as an image descriptor. The normalized histogram for every ring is calculated and saved as an image descriptor. After discarding the occluded part, the new normalized histogram is saved as an image descriptor. This histogram is used in the histogram matching by computing the histogram distance. The euclidean's distance is used to calculate the distance between target and reference image. The distance between target and reference image is calculated as:

$$d^{TR} = \sqrt{\alpha_1(TH_1 - RH_1)^2 + \ldots + \alpha_k(TH_k - RH_k)^2}\ . \tag{25}$$

where

TH_i = histogram of target image of ring $- i$,
RH_i = histogram of reference image of ring $- i$,
α_i = weighting factor of ring $- i$.

$\alpha_1, \alpha_2, \alpha_3, ..., \alpha_k$ are weighting factors (between 0 and 1) and denote the occlusion degree in every ring, 1 for no occlusion and 0 for occlusion at all. The reference image with the lowest distance is selected as matched image.

IV. EXPERIMENTS

The algorithm was evaluated to recognize the occluded, illumination change, shadowed, oblique, and rotated circular traffic signs. The tested images are taken from real scene using digital camera The images are taken in the daytime on the sunny and cloudy weather. Since the classification or recognition stage is investigated, the real sign image is selected in the rectangle size from the real scene image by manually using image software tools. The tested images consist of 180 images, some of those images are shown in fig. 7. The algorithm is implemented using MATLAB.

The figs. 8-11 show some of the specified gray scales images obtained from the target images. In every figure, the upper side shows the usual gray scale image and its histogram, the lower side shows the specified gray scale image obtained by the proposed method and its histogram.

In fig. 8 and fig. 9, two sign images with different illumination are shown. The histograms of the usual gray scale images show the difference in the range of gray scale. In fig. 9, where the image is darker than fig. 8, the gray scale for red and blue color is closer compared with the image in fig. 8. Meanwhile, the proposed specified gray scale images have the same range of gray scales. In the fig. 10, there are leaf shadows in the sign image. The proposed method can reconstruct the image properly. Fig. 11 shows the occluded image. The occluded object (tree) can be detected and shown as black object.

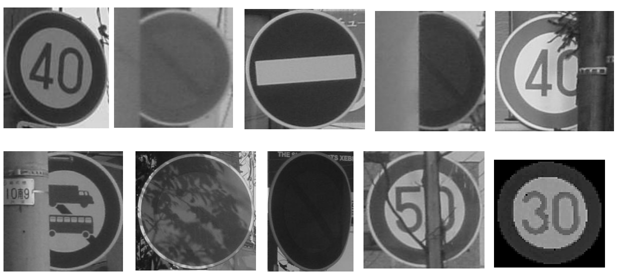


Figure 7. Some of the tested sign images.

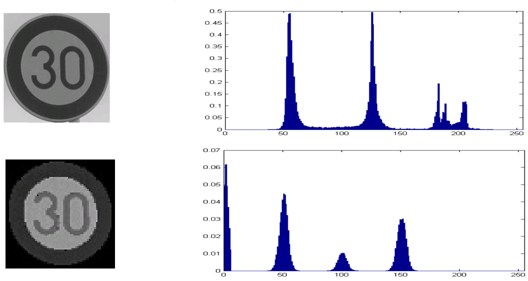


Figure 8. High brightness image.

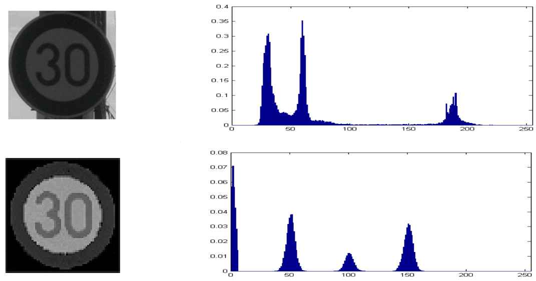


Figure 9. Low brightness image.

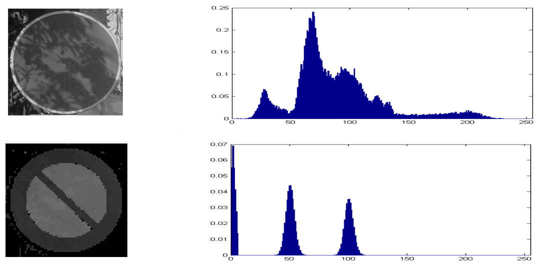


Figure 10. Shadowed image.

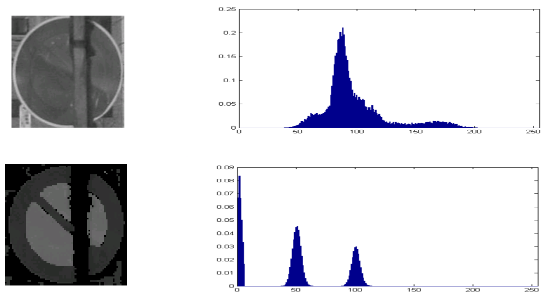


Figure 11. Occluded image.

In the matching process, six approaches are evaluated : histogram matching without partition, fuzzy histogram matching without partition, histogram matching with square partition, fuzzy histogram matching with square partition, histogram matching with ring partition, and fuzzy histogram matching with ring partition. Table 1 shows the experiment results.

Table 1 Matching results.

Method	Matching rate	Execution time
No partition		
Usual histogram	29.4 %	0.090 s
Fuzzy histogram	46.7 %	0.093 s
Square partition (3x3)		
Usual histogram	47.8 %	0.107 s
Fuzzy histogram	81.7 %	0.137 s
Ring partition (7 rings)		
Usual histogram	62.8 %	0.111 s
Fuzzy histogram	93.9 %	0.140 s

The result shows the effectiveness of ring partitioned method in the recognition of real sign images. Comparing with the usual histogram, the fuzzy histogram shows the better performance.

V. CONCLUSION

In this paper, we propose a method to classify the traffic sign image. First the RGB image is pre-processed using color thresholding and histogram specification technique to make a specified gray scale image. The specified gray scale image is invariant to the illumination changes. Then the ring partitioned method, which divide an image into several ring areas is used to match the image by computing the histogram for every ring. It follows from the experiment that the ring partitioned method shows the best performance in the matching of the occluded, rotated, shadowed, and illumination changes images, comparing with non-partitioned and square partitioned method. The color thresholding and specified histogram technique work effectively in the images with varying illumination and shadows. The fuzzy histogram technique affords the excelent result in the matching process regarding to the the imprecision, uncertainty of the real digital image .

From the experiment, the execution time is 0.14 second. The execution time can be faster if the algorithm is written in C languange instead of MATLAB. The proposed technique provides a simple algorithm, therefore the real time implementation can be achieved.

The problems which may arise using this proposed classification technique are segmentation of traffic sign according to the certain color and detecting the occluded object for various traffic sign images and occluded objects. The proposed classification method is part of a traffic sign recognition system. The future works will cover the detection stage of traffic signs and classification for another type of traffic signs, such rectangular signs and triangular signs.

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