www.s2is.org
International Journal on Smart Sensing and Intelligent Systems
ISSN 1178-5608

CIRCULAR TRAFFIC SIGN CLASSIFICATION USING HOG-BASED RING PARTITIONED MATCHING

Aryuanto Soetedjo, I Komang Somawirata
Department of Electrical Engineering
National Institute of Technology (ITN) Malang
Jalan Raya Karanglo Km 2 Malang, Indonesia
Emails: aryuanto@gmail.com; kmgsomawirata@yahoo.com

Submitted: June 2, 2017 ***Accepted: July 27, 2017*** ***Published: Sep. 1, 2017***

Abstract- This paper presents a technique to classify the circular traffic sign based-on HOG (histogram of oriented gradients) and a ring partitioned matching. The method divides an image into several ring areas, and calculates the HOG feature on each ring area. In the matching process, the weight is assigned to each ring for calculating the distance of HOG feature between tested image and reference image. The experimental results show that the proposed algorithm achieves a high classification rate of 97.8%, without the need of many prepared sample images. The results also show that the best values of the number of orientation bins and the cell size of the HOG parameters are 5 and 10 x 10 pixels respectively.

Index terms: HOG, traffic sign classification, ring partitioned, template matching.

I. INTRODUCTION

Driver Assistant System (DAS) is one of interesting applications in the Intelligent Transportation System (ITS). The aim of DAS is to provide a safety driving to the driver, such as to monitor the driver fatigue [1], detect the road lane [2], and recognize the traffic signs [3-16]. Traffic sign recognition (TSR) system is one of the popular and challenging topics in the DAS. Basically, TSR consists of two steps [3-16]: traffic sign detection and classification. Traffic sign detection is used to detect the appearance of the traffic sign on an image. It localizes the position of traffic signs for further process, i.e. the classification process. In the classification process, the traffic sign is classified into the predefined one, such as the 50 km/h speed limit sign, the stop sign, etc. This paper deals with the classification of traffic signs, specifically the circular traffic signs as treated in [4], [10], [14], [17].

Traffic sign classification is not an easy task due to the several reasons [13]: a) a large numbers of traffic sign classes; b) it is difficult to provide many samples of a predefined traffic sign required by a supervised machine learning; c) similarity among the traffic signs on a category; d) real-time requirement in the DAS; e) problems of illumination changes, partial occlusion, and physical damage.

Several approaches are proposed for classifying the traffic sign, which could be grouped into two categories [10]: classifier-based methods and template-based methods. The classifier-based methods use the machine learning classifiers, such as the Support Vector Machine (SVM) [3-10], the random forest [11], the Artificial Neural Network (ANN) [12-14], [18], [19], and the AdaBoost algorithm [15]. The template-based methods use the cross-correlation algorithm [16] and the histogram matching [17].

In [3], a SVM with bagged kernels was used to recognize the traffic sign on a region of interest defined by the detection stage which was performed by the color segmentation and the shape matching. The SVM was employed to classify the digit of speed limit sign [4]. The SVM was trained by the curve feature which represented the pixel’s intensity of digit number in each column. The Histogram of Oriented Gradient (HOG) feature was used as the descriptors of the SVM [5-7]. In [8], two SVMs with Gaussian kernels were employed to detect the traffic signs. The SVMs consisted of one SVM for triangular signs and one SVM for circular signs. In [9], the

SVM for red color signs and the SVM for blue color signs were adopted to increase the classification accuracy. The approach took the benefit of reducing the number of classes to be trained by separating the red and blue signs. An ensemble of HOG, Local Binary Patterns (LBP), and Gabor features with SVM classifier was proposed in [10]. The results showed that classification rate increased compared with the single HOG feature. However, the classification time was much slower. The HOG feature with a random forest classification was proposed in [11]. The method achieved the highest classification rate compared with the SVM and the ANN, while the classification time was fastest.

The ANN based feature dimension reduction and classification was employed in [12] to classify the traffic signs. It reduced the features by employing the ANN based K-mean clustering, then classifying them using the ANN. The Convolutional Neural Network (CNN), a neural network that use a convolutional layer for extracting the features, was employed in [13], [14]. To speed up the convergence, a cascade configuration of the CNN was developed in [18]. The Extreme Learning Machine (ELM), a learning classifier that uses the random mapping between the input layer and the hidden layer, was employed in [19]. The approach showed the balance results of the classification accuracy and the computation time. The SimBoost, a variant of AdaBoost algorithm was proposed in [15]. It measured the similarity of images which was learned from the image pairs.

The classifier-based methods are the effective methods to classify the traffic sign. However, there are several drawbacks such as: they need a huge numbers of sample images in the training process, and the training process is time consuming. Based on the work in [5], the classification rate increases 27.67%, when the number of training samples is increased from 150 samples to 207 samples. In [17], the classification rate increases 7.15%, when the number of training samples is increased from 50 samples to 135 samples. The comparison of the training time and the classification time was conducted in [12], where the training time was 1800 seconds, while the classification time was 0.005 seconds.

The template-based method is a simple method for classifying the traffic sign. It does not require a training process and the training samples. Instead, it only needs the reference images, in which the traffic sign will be classified. To increase the classification rate and cope with the occlusion, rotation, and illumination changes problems, the fuzzy histogram and the ring-partitioned matching was proposed in [17].

The other important factor should be considered in the classification process is the features extraction. The features commonly used are the image histogram [3], [17]; the Histogram of Oriented Gradient (HOG) [5-7], [10], [11], [15], [19]; the intensity of image pixels [9], [14], [16], [18]; and the haar wavelet [15].

This paper proposes a novel technique to classify the circular traffic sign using the template-based method by employing the ring partitioned matching, which is inspired by our previous work [17] and the HOG descriptor. In the proposed method, the HOG feature is extracted from an image, and the distances of HOG vectors on each ring area of the image between a test image and the reference images are calculated to find the best matching. The benefits of our method are: a) the training process and the training samples are not needed; b) the HOG describes the image feature effectively; c) the ring partitioned method provides an effective way in the matching calculation by introducing the weights on the ring areas.

The main contributions of the paper are in developing the simple effective method to classify the (red) circular traffic signs without preparing the training images, and in examining the effects of the HOG parameter and the ring number in the classification process.

The rest of paper is organized as follows. Section II presents the related work in the traffic sign classification. Section III describes the proposed method. The experimental results are presented in section IV. Finally, the conclusion is covered in section V.

II. RELATED WORK

a. Traffic Sign Classification based on HOG Feature

HOG is a descriptor introduced by [20] to detect pedestrian. It computes the occurrence of orientation of gradient in an image. The feature is easy to be calculated and invariant to illumination and scale changes. Therefore many traffic sign classification techniques adopted this descriptor [5-7], [10], [11], [15], [19].

In [5-7], [10], the HOG was adopted as the feature extraction for the SVM classification. In [5], the image was resized into 32 x 32 pixels, and the HOG feature was extracted from the blocks, where each block was divided into 4 x 4 cells, and each cell consisted of 4 x 4 pixels. The number of orientation bins was 6. In the classification process, the SVM with one-against-all method was employed for multi-class classification. The results showed that the HOG is the good descriptor for classifying the traffic signs.

In [6], a cascade of SVM classifier was used to classify the traffic signs. The HOG feature was extracted from the resized image of 24 x 24 pixels. The cell size was 8 x 8 pixels, the block size was 2 x 2 cells, and the bins number was 9. At first, the HOG feature was used to classify the traffic sign according to the shape, i.e. circle, rectangle, triangle, upside-down triangle. Then it was classified using the sub-classifier for the specific shape such as color circle classifier, color rectangle classifier, while circle classifier, white triangle classifier, white upside-down triangle classifier, and white rectangle classifier.

In [7], the HOG feature was extracted from the resized image of 32 x 32 pixels. The cell size was 12 x 12 pixels, the block size was 4 x 4 cells, and the bins number was 9. The SVM classifier adopted the one-against-one and a voting scenario for multi-class classification.

A variant of HOG feature (called as HOGv) with the ELM (extreme learning machine) classifier was developed in [19]. The improvements of HOGv involve two parts. First, it included both the signed orientation of gradient (contrast sensitive) and the unsigned orientation of gradient (contrast insensitive). Second, the resulted features were reduced using the Principal Component Analysis (PCA). The approach was proposed to overcome the problem of the redundancy and the local details of the descriptor. Further they showed that the ELM classifier has superiority in both the classification rate and execution time compared with the SVM.

b. Traffic Sign Classification using Ring Partitioned Matching

Our previous work in [17] developed a ring partitioned matching to classify the circular traffic signs. The technique employed the fuzzy histogram and a ring partitioned method. An image was partitioned into ring areas as illustrated in figure 1. The fuzzy histogram was computed on each ring. Then the histogram matching between the test image and the reference images was calculated on each ring using the Euclidean distance.

Soetedjo [17] proved that in the case of image histogram, a better descriptor was obtained when the image is partitioned into several sub-images. By partitioning into ring shape areas, the histogram of image does not change when the image is rotated. Further, the partitions allowed us to give the different weights in the matching process. The results showed that the method worked effectively in classifying the traffic signs under the problems of partial occlusions, rotated, and illumination changes, without preparing the training images.

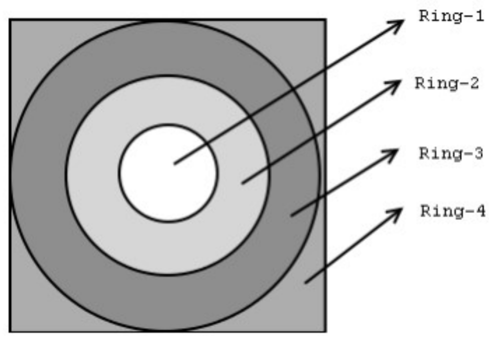

Figure 1. Ring partition [17]

III. PROPOSED METHOD

In this paper, we propose the circular traffic sign classification method by combining the HOG feature and the ring partitioned matching. The main objective is to develop a technique to classify traffic signs without the need of prepared many samples images. The proposed method exploits the benefits of the HOG feature [20] and the ring partitioned matching [17]. More specifically, the HOG feature provides an effective descriptor of the image under the varying illumination problem. While, the ring partitioned matching provides an effective way to emphasize the certain ring areas in the matching as described in the following.

a. HOG Feature

The HOG describes the histogram of orientation of gradient in the image [20]. This feature is extracted from the image using blocks and cells as illustrated in figure 2. To calculate HOG, an image is divided into blocks, where the block may overlap with its neighbors. Each block is divided into non-overlapping pixels called cells. Histogram contains of magnitude and orientation of gradient of image in each cell is calculated. According to Dalal [20], the number of bins to quantize the orientation of gradient is nine for the best result. The HOG feature of a whole image is obtained by concatenating the histograms from each cell and the block.

In this paper, the traffic sign image is resized into 80 x 80 pixels. The cell size varies from 4 x 4 pixels to 10 x 10 pixels, the block size is 2 x 2 cells, and the number of orientation bins varies from 3 to 12. The visualization of HOG feature for the 30 km/h speed limit sign is shown in figure 3. It is noted that the HOG feature is obtained from the grayscale image, i.e. the gradient of image is calculated from the grayscale image.

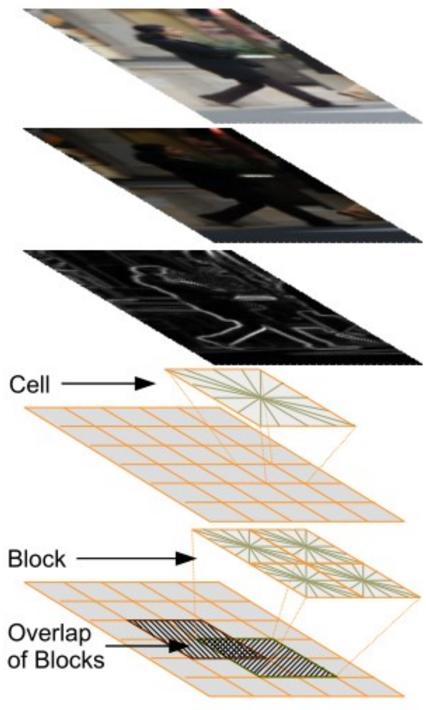

Figure 2. Structure of HOG feature [21]

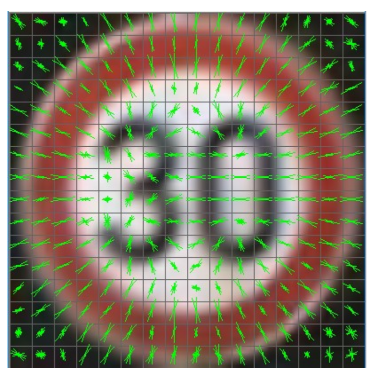

Figure 3. Visualization of HOG feature

.

b. Ring Partitioned Matching

As described previously, the HOG feature is usually used in conjunction with the machine learning classifiers such as SVM, ANN, etc. In this work, we employ the HOG feature as the image descriptor for the traffic sign classification using the ring partitioned matching.

The ring partitioned matching is originally proposed in our previous work [17] to cope with the occluded and rotated images. In the previous work, since the image histogram is employed, the property of rotation invariant is hold. However, the HOG feature is not rotation invariant. Therefore, in this paper we only consider the traffic signs with a small rotation problem, In fact, the traffic signs usually appear in upright position as addressed by Greenhalgh [6], where the rotation problem could be avoided.

In this work, we treat the ring partitioned matching in slightly different with the previous work. Here, the main idea is to exploit the ring partition method for giving the different weights on ring areas. More clearly, since the image is partitioned into several ring areas as illustrated in figure 1 and figure 2, we may give more attention on the inner area than the outer area. Specifically, for the red circular traffic signs such as the speed limit signs, the outer ring area is almost similar, i.e. the red circle. While the information of speed sign is contained in the inner ring area.

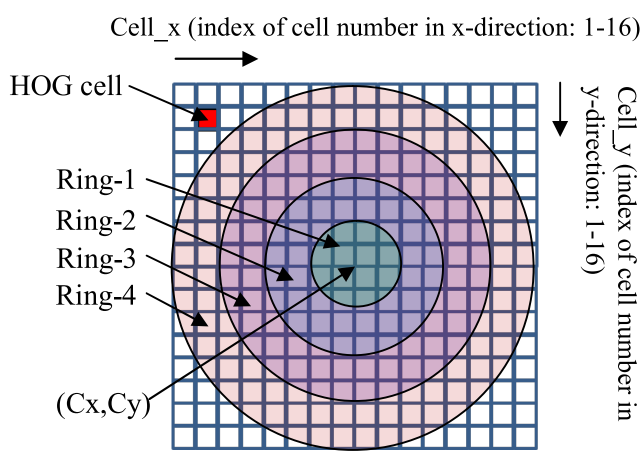

Figure 4. Ring areas and HOG cells of an image

Figure 4 illustrates the ring areas and HOG cells of an image. In this example, the image size is 80 x 80 pixels and the cell size is 5 x 5 pixels. Thus the image is divided into 16 x 16 cells as shown in the figure. Since the calculation of HOG feature is based on the cells (and the blocks), the HOG feature of each ring is calculated based-on the cells that are belong to the ring as discussed in the following.

The HOG feature of each ring is calculated as follows:

(1) Calculate histogram of gradient on each cell,

(2) Normalize the histogram on the block to obtain the HOG feature of the cell,

(3) Save the HOG feature of each cell,

(4) Assign the cell into a ring number,

(5) Concatenate the histograms of the cells on the same ring.

As shown in figure 4, since the cell size is 5 x 5 pixels (not a single pixel) and the ring shape is a circle, the ring area may not cover a whole cell. To assign the cell into a ring, we employ the following formulas. Let *Cx, Cy* are the center coordinates of the image in *x*-coordinate and *y*-coordinate respectively; *Cell_x, Cell_y* are the index of cell number in *x*-coordinate and *y*-coordinate respectively; *Im_width, Cell_width* are the widths of image and cell respectively; *Ring_num* is the number of ring; and *n* is the index of ring (*n*=1 to *Ring_num*). The radius of ring-*n* is defined as *Rn* and expressed

$$Rn = n \times \frac{Im\_width / Cell\_width}{2 \times Ring\_num} \qquad (1)$$

The cell distances from *Cx* and *Cy* are defined as *Dist_x* and *Dist_y*, which are expressed by equations (2) and (3).

$$\begin{aligned}&\text{If } Cell\_x \le Cx \text{ then } Dist\_x = Cx + 1 - Cell\_x,\\ &\text{else } Dist\_x = Cell\_x - Cx\end{aligned} \qquad (2)$$

$$\begin{aligned}&\text{If } Cell\_y \le Cy \text{ then } Dist\_y = Cy + 1 - Cell\_y,\\ &\text{else } Dist\_y = Cell\_y - Cy\end{aligned} \qquad (3)$$

To assign a cell (*Cell_x,Cell_y*) into a ring, the condition expressed in equation (4) is employed.

$$\begin{aligned}&\text{If } (Rn)^2 < (Dist\_x)^2 + (Dist\_y)^2 \le (R(n+1))^2\\ &\text{then the index of ring is } (n+1)\end{aligned} \qquad (4)$$

To match between the tested image and reference image, the Euclidean distance is employed. The distance between tested and reference images is defined as *d*(*T,R*), and expressed as

$$d(T,R) = \sqrt{\sum_n w_n \left(\sum_{f(n)} ((THOG_n(f(n)) - RHOG_n(f(n)))^2 \right)} \qquad (5)$$

where *n* is the ring number; *f*(*n*) is the number of HOG vectors of ring-*n*; *THOGn*(.) is the HOG feature of tested image of ring-*n*; *RHOGn*(.) is the HOG feature of reference image of ring-*n*; w_n is the weight of ring-*n*.

IV. EXPERIMENTAL RESULTS

Several experiments are conducted to verify our proposed method. In the experiments, we deals with ten red circular traffic signs as depicted in figure 5. The images are obtained from GTRSB dataset [22]. The total number of tested images is 1000 images. There are 100 images for each type of red circular traffic sign. The algorithm is implemented using C++ and OpenCV [23] running on a personal computer Intel Core i7 3.4 Ghz.

Figure 5. Ten red circular traffic sign images (taken from GTRSB dataset [22]

In the experiments, we compare our proposed HOG-Ring partitioned matching (**HOG-Ring**) with the HOG method without ring partitioned (**HOG-NoRing**). In each method, the number of orientation bins varies from 3, 5, 9, and 12. While the cell size varies from 4 x 4 pixels, 5 x 5 pixels, 8 x 8 pixels, and 10 x 10 pixels. In **HOG-Ring** method, the number of ring varies from 2, 3, 4, and 5. In each ring number, two different sets of weights are examined.

During experiments, the classification rate and execution time are calculated. The result of **HOG-NoRing** is given in Table 1. The results of **HOG-Ring** are given in Table 2 to Table 9. Table 2 and Table 3 are the results when the ring number of 2, set of weights-1 (w_1=0.75; w_2=0.25) and set of weights-2 (w_1=0.25; w_2=0.75). Table 4 and Table 5 are the results when the ring number of 3, set of weights-1 (w_1=0.5; w_2=0.5; w_3=0.25) and set of weights-2 (w_1=0.25; w_2=0.75; w_3=0.25). Table 6 and Table 7 are the results when the ring number of 4, set of weights-1 (w_1=0.25; w_2=0.75; w_3=0.5; w_4=0.25) and set of weights-2 (w_1=0.25; w_2=0.75; w_3=0.25; w_4=0). Table 8 and Table 9 are the results when the ring number of 5, set of weights-1 (w_1=0.25; w_2=0.75; w_3=0.5; w_4=0.25; w_5=0.25) and set of weights-2 (w_1=0.25; w_2=0.5; w_3=0.75; w_4=0.25; w_5=0).

Examining the tables, it is worthy to note that for all cases, the number of bins of 5 gives the best classification rate for the particular case. While the number of bins of 12 is the worst. The results imply that too many bins of the orientation of gradient yields the HOG feature that is sensitive to noise. The image noise or more details of symbol in the image may be extracted in the HOG feature, so that it produces the misclassification. On the other hand, when the number of bins is very small, i.e 3, the number of extracted features is limited. In this case, several images may have the similar HOG feature that results the misclassification.

The effect of cell size could be examined from the tables, where increasing the size will increase the classification rate (except for the number of bins of 3). The results could be understood from the fact that by increasing the cell size will produce the less details of the feature in the image. It yields the better descriptor of the image and produces the higher classification rate.

The results in Table 1 show that the HOG feature is an effective descriptor for matching the circular traffic signs, even though without no machine learning. It is clearly shown from the tables that the classification rate of the **HOG-Ring** is superior to the **HOG-NoRing**. From the experiments, the highest classification rate of the **HOG-NoRing** is 95.4%, (Table 1) while the highest classification rate of the **HOG-Ring** is 97.8% (Table 2 and Table 9). As shown in tables, this highest result is obtained when the number of bins is 5 and the cell size is 10 x 10 pixels.

Table 1: Result of HOG-Without Ring Partitioned

HOG-NoRing			
Number of orientation bins	**Cell size (pixels)**	**Classification rate (%)**	**Execution time (ms)**
Bins=3	4 x 4	91.2	29.38
	5 x 5	90.1	21.86
	8 x 8	90.4	14.39
	10 x 10	86.9	13.38
Bins=5	4 x 4	91.9	41.51
	5 x 5	93.0	28.97
	8 x 8	94.2	16.89
	10 x 10	**95.4**	14.51
Bins=9	4 x 4	89.6	66.25
	5 x 5	91.2	52.82
	8 x 8	93.1	22.67
	10 x 10	95.4	17.63
Bins=12	4 x 4	87.1	88.92
	5 x 5	89.0	54.57
	8 x 8	92.6	26.01
	10 x 10	93.7	21.50

Table 2: Result of HOG-With Ring Partitioned (R2_1)

HOG-Ring: Ring number=2; Weights=(0.75;0.25)			
Number of orientation bins	**Cell size (pixels)**	**Classification rate (%)**	**Execution time (ms)**
Bins=3	4 x 4	93.4	67.02
	5 x 5	94.2	46.50
	8 x 8	94.9	21.63
	10 x 10	91.7	18.09
Bins=5	4 x 4	94.7	86.65
	5 x 5	95.3	56.89
	8 x 8	96.9	27.65
	10 x 10	**97.8**	21.35
Bins=9	4 x 4	93.7	109.98
	5 x 5	94.5	75.22
	8 x 8	96.8	35.26
	10 x 10	97.4	29.00
Bins=12	4 x 4	92.1	157.92
	5 x 5	94.1	95.33
	8 x 8	95.6	45.08
	10 x 10	95.6	33.40

Table 3: Result of HOG-With Ring Partitioned (R2_2)

HOG-Ring: Ring number=2; Weights=(0.25;0.75)			
Number of orientation bins	**Cell size (pixels)**	**Classification rate (%)**	**Execution time (ms)**
Bins=3	4 x 4	89.9	69.32
	5 x 5	91.2	47.94
	8 x 8	87.8	21.39
	10 x 10	84.8	18.17
Bins=5	4 x 4	87.2	88.32
	5 x 5	**93.6**	59.81
	8 x 8	91.4	27.09
	10 x 10	90.9	20.65
Bins=9	4 x 4	84.4	111.50
	5 x 5	91.0	78.52
	8 x 8	90.1	36.29
	10 x 10	89.0	29.32
Bins=12	4 x 4	81.8	154.91
	5 x 5	89.1	98.59
	8 x 8	88.9	45.94
	10 x 10	86.0	35.59

Table 4: Result of HOG-With Ring Partitioned (R3_1)

HOG-Ring: Ring number=3; Weights=(0.5;0.5;0.25)			
Number of orientation bins	**Cell size (pixels)**	**Classification rate (%)**	**Execution time (ms)**
Bins=3	4 x 4	94.2	61.25
	5 x 5	93.3	38.15
	8 x 8	93.9	20.88
	10 x 10	92.3	24.34
Bins=5	4 x 4	94.4	94.04
	5 x 5	93.4	53.30
	8 x 8	94.5	28.42
	10 x 10	**96.3**	20.71
Bins=9	4 x 4	92.9	115.78
	5 x 5	90.9	78.50
	8 x 8	93.1	37.14
	10 x 10	95.3	27.76
Bins=12	4 x 4	91.9	149.66
	5 x 5	90.0	99.76
	8 x 8	93.3	44.17
	10 x 10	93.8	33.34

Table 5: Result of HOG-With Ring Partitioned (R3_2)

HOG-Ring: Ring number=3; Weights=(0.25;0.75;0.25)			
Number of orientation bins	**Cell size (pixels)**	**Classification rate (%)**	**Execution time (ms)**
Bins=3	4 x 4	93.6	60.72
	5 x 5	94.6	38.54
	8 x 8	93.0	21.26
	10 x 10	89.2	24.71
Bins=5	4 x 4	93.9	89.61
	5 x 5	95.6	53.30
	8 x 8	95.5	28.75
	10 x 10	95.8	22.05
Bins=9	4 x 4	92.7	115.26
	5 x 5	93.6	78.64
	8 x 8	94.9	36.10
	10 x 10	**96.0**	28.05
Bins=12	4 x 4	91.5	152.86
	5 x 5	92.4	103.49
	8 x 8	93.6	45.25
	10 x 10	93.7	32.82

Table 6: Result of HOG-With Ring Partitioned (R4_1)

HOG-Ring: Ring number=4; Weights=(0.25;0.75;0.5;0.25)			
Number of orientation bins	**Cell size (pixels)**	**Classification rate (%)**	**Execution time (ms)**
Bins=3	4 x 4	94.4	63.63
	5 x 5	94.4	42.69
	8 x 8	91.7	21.50
	10 x 10	91.9	18.42
Bins=5	4 x 4	94.2	77.05
	5 x 5	95.7	54.52
	8 x 8	95.1	26.83
	10 x 10	**97.1**	21.09
Bins=9	4 x 4	93.2	124.99
	5 x 5	93.7	91.67
	8 x 8	93.7	39.20
	10 x 10	95.4	28.73
Bins=12	4 x 4	91.7	162.55
	5 x 5	92.6	114.88
	8 x 8	93.3	52.07
	10 x 10	93.9	32.79

Table 7: Result of HOG-With Ring Partitioned (R4_2)

HOG-Ring: Ring number=4; Weights=(0.25;0.75;0.5;0)			
Number of orientation bins	**Cell size (pixels)**	**Classification rate (%)**	**Execution time (ms)**
Bins=3	4 x 4	94.8	62.74
	5 x 5	95.3	40.24
	8 x 8	93.4	22.45
	10 x 10	93.1	17.85
Bins=5	4 x 4	95.4	76.37
	5 x 5	96.0	54.46
	8 x 8	96.3	26.60
	10 x 10	**97.4**	20.97
Bins=9	4 x 4	94.2	124.86
	5 x 5	94.2	83.31
	8 x 8	95.7	37.73
	10 x 10	96.5	28.35
Bins=12	4 x 4	92.5	168.54
	5 x 5	93.2	118.92
	8 x 8	94.2	48.86
	10 x 10	94.5	32.99

Table 8: Result of HOG-With Ring Partitioned (R5_1)

HOG-Ring: Ring number=5; Weights=(0.25;0.75;0.5;0.25;0.25)			
Number of orientation bins	**Cell size (pixels)**	**Classification rate (%)**	**Execution time (ms)**
Bins=3	4 x 4	94.2	53.98
	5 x 5	95.3	39.34
	8 x 8	95.2	22.60
	10 x 10	92.1	18.94
Bins=5	4 x 4	95.0	96.95
	5 x 5	95.9	50.84
	8 x 8	**96.7**	27.61
	10 x 10	96.5	21.76
Bins=9	4 x 4	93.7	118.52
	5 x 5	94.4	80.21
	8 x 8	96.3	39.68
	10 x 10	95.4	28.46
Bins=12	4 x 4	92.1	154.70
	5 x 5	93.2	106.79
	8 x 8	94.5	45.96
	10 x 10	93.6	37.09

Table 9: Result of HOG-With Ring Partitioned (R5_2)

HOG-Ring: Ring number=5; Weights=(0.25;0.5;0.75;0.25;0)			
Number of orientation bins	**Cell size (pixels)**	**Classification rate (%)**	**Execution time (ms)**
Bins=3	4 x 4	94.9	53.83
	5 x 5	95.7	39.63
	8 x 8	95.4	22.69
	10 x 10	91.9	19.23
Bins=5	4 x 4	95.6	97.18
	5 x 5	96.0	50.51
	8 x 8	96.3	27.93
	10 x 10	**97.8**	21.32
Bins=9	4 x 4	94.3	124.55
	5 x 5	93.8	80.20
	8 x 8	96.0	42.45
	10 x 10	97.4	28.67
Bins=12	4 x 4	92.9	152.10
	5 x 5	92.8	101.50
	8 x 8	95.2	47.16
	10 x 10	95.9	34.66

To see the effectiveness of ring partitioned matching, let us compare the results in Table 1, Table 2, and Table 3. In this discussion, the number of bins of 5 and the cell size of 10 x 10 pixels are used. From Table 1, when there is no ring partitioned, the classification rate is 95.4%. When the matching is calculated using ring partitioned method (the number of ring is 2), then two different results are obtained. If the weights on ring-1 and ring-2 are set to 0.25 and 0.75, the classification rate is 90.9% (see Table 3). However, if the weights are set to 0.75 and 0.25, the classification rate increases to 97.8% (see Table 2). It suggests that by partitioning the image into several ring areas and by selecting the proper weights, the classification rate could be increased effectively. In fact, the proper weights could be defined from the information or symbol contained in the image. In the case of traffic signs shown in Fig. 5, we may refer to Table 7 or Table 9 for selecting the weights for the best result, where the innermost ring (ring-1) and the outermost ring (ring-4) are given less weights than the other rings (ring-2 and ring-3).

Concerning with the execution time, it is obtained that the execution time decreases when the cell size increases. By increasing the cell size, the number of HOG feature will decrease, thus it reduces the execution time in calculating the distance during matching process. It is also obtained that by increasing the number of bins will increase the number of HOG feature, thus it increases the execution time. Comparing the execution time of **HOG-Ring** and the **HOG-NoRing**, the execution time of **HOG-Ring** is about two times slower than the **HOG-NoRing**. It is caused by the image scanning process in the **HOG-Ring**, which is done twice. The first scanning is to calculate the HOG feature of all cells in the image, and the second scanning is to assign the cells into the ring numbers. To speed up the execution time, both processes could be done simultaneously, and will be addressed for further work.

V. CONCLUSION

The HOG feature and ring partitioned matching was developed to classify the red circular traffic signs. In the experiments, several parameters such as the number of rings, the number of orientation bins, the cell size, and the set of weights were examined. The number of rings and the set of weights should be defined properly to produce the high classification rate. The results show that the proposed method provides an effective method in the circular traffic sign classification, without the need many sample images. In future, the method will be extended to cope with the other traffic signs under the complex problems. Further, the algorithm to speed up the execution time will be developed.

ACKNOWLEDGMENT

This work is supported by the Research Grant 2017, Competence-Based Research scheme from Directorate General of Higher Education, Ministry of Research and Technology and Higher Education, Republic of Indonesia, No.: SP DIPA-042.06.1.401516/2017.

REFERENCES

[1] A. Soetedjo and I.K. Somawirata, “Implementation of eye detection using dual camera on the embedded system,” International Journal of Innovative Computing, Information and Control (IJICIC), Vol. 13, No. 2, pp. 397-409, 2017.

[2] X. Miao and S.L. Huan Shen, “On-board lane detection system for intelligent vehicle based on monocular vision,” International Journal on Smart Sensing and Intelligent Systems, Vol. 5, No. 4, pp. 957-972, 2012.

[3] S.B. Wali, M.A. Hannan, A. Hussain and S.A. Samad, “An automatic traffic sign detection and recognition system based on colour segmentation, shape matching, and SVM,” Mathematical Problems in Engineering, Vol. 2015, pp. 1-11, 2015.

[4] R. Biswas, H. Fleyeh and M. Mostakim, “Detection and classification of speed limit traffic signs,” Proceedings of 2014 World Congress on Computer Applications and Information Systems (WCCAIS), Hammamet, Tunisia, 2014, pp. 1-6.

[5] A. Adam and C. Ioannidis, “Automatic road-sign detection and classification based on support vector machines and HOG descriptors,” ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Vol. II-5, pp. 1-7, 2014.

[6] J. Greenhalgh and M. Mirmehdi, “Real-time detection and recognition of road traffic signs,” IEEE Trans. on Intelligent Transportation Systems, Vol. 13, No. 2, pp. 1498-1506, 2012.

[7] N.B. Romdhane, H. Mliki and M. Hammami, “An improved traffic signs recognition and tracking method for driver assistance system,” Proceedings of 2016 IEEE/ACIS 15th

International Conference on Computer and Information Science (ICIS), Okayama, Japan, 2016, pp. 1-6.

[8] M.A. García-Garrido, M. Ocana, D.F. Llorca, E. Arroyo, J. Pozuelo and M. Gavilan, "Complete vision-based traffic sign recognition supported by an I2V communication system," Sensors, Vol. 12, Issue 2, pp. 1148-1169, 2012.

[9] T. Bui-Minh, O. Ghita, P. F. Whelan and T. Hoang, "A robust algorithm for detection and classification of traffic signs in video data," Proceedings of 2012 International Conference on Control, Automation and Information Sciences (ICCAIS), Ho Chi Minh City, Vietnam, 2012, pp. 108-113.

[10] S.K. Berkaya, H. Gunduz, O. Ozsen, C. Akinlar and S. Gunal, "On circular traffic sign detection and recognition," Expert Systems with Applications, Vol. 48, pp. 67-75, 2016.

[11] J. Greenhalgh and M. Mirmehdi, "Traffic sign recognition using MSER and random forests," Proceedings of 20th European Signal Processing Conference (EUSIPCO 2012), Bucharest, Romania, 2012, pp. 1935-1939.

[12] S. Yin, P. Ouyang, L. Liu, Y. Guo and S. Wei, "Fast traffic sign recognition with a rotation invariant binary pattern based feature," Sensors, Vol. 15, Issue 1, pp. 2161-2180, 2015.

[13] I. Filkovic, "Traffic sign localization and classification methods: an overview," [Online]. Available: https://www.fer.unizg.hr/_download /repository/ KDI,_Ivan_Filkovic.pdf

[14] M. Peemen, B. Mesman and H. Corporaal, "Speed sign detection and recognition by convolutional neural networks," Proceedings of 8th International Automotive Congress, Eindhoven, Nederland, 2011, pp. 162–170.

[15] A. Ruta, F. Porikli, S. Watanabe and Y. Li, "In-vehicle camera traffic sign detection and recognition," Machine Vision and Applications, Vol. 22, pp. 359–375, 2011.

[16] R. Laguna, R. Barrientos, L.F. Blazquez and L.J. Miguel, "Traffic sign recognition application based on image processing techniques," Proceedings of the 19th World Congress The International Federation of Automatic Control, Cape Town, South Africa. August 24-29, 2014, pp. 104-109.

[17] A. Soetedjo and K. Yamada, "Traffic sign classification using ring-partitioned matching," IEICE Trans. Fundamentals, Vol. E88-A, No. 9, pp. 2419-2426, 2005.

[18] R.F. Rachmadi, Y. Komokata, K. Uchimura, and G. Koutaki, "Road sign classification system using cascade convolutional neural network," International Journal of Innovative

Computing, Information and Control, Vol. 13, No. 1, pp. 95-109, 2017.

[19] Z. Huang, Y. Yu, J. Gu and H. Liu, “An efficient method for traffic Sign recognition based on extreme learning machine,” IEEE Transactions on Cybernetics, Vol. 47, Issue 4, pp. 920-933, 2017.

[20] N. Dalal and B. Triggs, "Histograms of oriented gradients for human detection," Proceedings of 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05), Vol. 1, San Diego, CA, USA, 2005, pp. 886-893.

[21] N. Dalal, “Finding people in images and videos,” PhD thesis, INRIA, French, 2006.

[22] J. Stallkamp, M. Schlipsing, J. Salmen and C. Igel. “The German Traffic Sign Recognition Benchmark: A multi-class classification competition,” Proceedings of the IEEE International Joint Conference on Neural Networks, San Jose, CA, USA, 2011, pp. 1453–1460.

[23] http://opencv.org/