Intra color-shape classification for traffic sign recognition

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***Abstract*— This paper presents a novel traffic sign recognition system comprising of: (i) Color/shape classification, (ii) Pictogram extraction, (iii) Features selection and, (iv) Lyapunov Theory-based Radial Basis Function neural network (RBFNN). In the proposed system, traffic signs are first segmented and classified with regard to its unique color and shape in order to partition a large set of data into smaller subclasses. Within these subclasses, all redundant information except the pictogram is discarded for feature selection since the pictogram contains critical information for road users. Principle Component Analysis (PCA) is applied to extract salient points for traffic sign dimensionality reduction. This is followed by the Fisher's Linear Discriminant (FLD) to further obtain the most discriminant features. These features are fed into RBFNN for training with a proposed weight updating scheme based on Lyapunov stability theory. The performance of the proposed system is evaluated with Malaysian road signs with promising recognition rate.**

Keywords- Advanced driver assistance system, Traffic sign recognition, and Classificaiton.

I. INTRODUCTION

Traffic sign recognition (TSR) has recently drawn a great attention in vehicular technology as an advanced driver assistance mechanism to increase a driver's awareness towards hazardous road conditions [1]. This system is mainly designed to detect and interpret road signs automatically to inform a driver of the presence of the signs and give instant feedback for the critical circumstances. Neglect or failure of reading road sign may consequent in road accidents and economical lose. Therefore, with the aid of TSR, it may reduce these impacts and at the same time, it improves the transportation safety and navigation efficiency. Moreover, the application of TSR on a moving vehicle may indirectly regulate the traffic flow and reduce the possibility of traffic congestion.

Traffic sign classification techniques play an important role in identifying the useful information given from a sign. In recent years, neural networks, for instance, Multilayer neural network (MLNN), Radial Basis Function neural network (RBFNN), and Support Vector Machine (SVM) are popular methods for the classification of road signs. Bascon et al. [1] proposed a road sign content recognition for Spanish traffic-signs using Gaussian-kernel SVMs. In addition, Jimenez et al. [2] computed the projection of the objects and applied SVMs to recognize the pictogram shape for Spanish circular signs. Shi et al. [3] performed a traffic sign recognition using SVMs for Swedish road signs in two kinds of features representation, i.e. binary image and Zernike moments.

Besides that, Escalera et al. [4] used a color ratio thresholding and a corner detection on an RGB image to extract the traffic signs. Two MLNNs were hence utilized to classify only nine circular and triangular signs respectively. Vicen-Bueno et al. [5] performed image dimension reduction before passing to neural networks for classification. Furthermore, Medici et al. [6] applied a contrast stretching technique on the extracted regions and recognized the unknown signs using MLNNs for Italian road signs. Broggi et al. [7] presented a road signs detection and classification associating with color segmentation, shape recognition and a lightweight neural network. Additionally, Wang et al. [8] adopted RBF networks for traffic sign classification. They created traffic signs with artificial transformation to possibly imitate the real scene traffic signs in order to train the test their neural classifiers.

In this paper, a novel TSR system including color/shape classification, pictogram extraction, feature selection and Lyapunov theory-based RBFNN is demonstrated in Fig. 1. The concern of this paper will be mainly focusing on the classification stage. To overcome the issue of relatively large traffic sign database, the segmented traffic signs are initially determined with color histogram to split them into the subgroups. It is followed by the shape identifier to further partition the large volume of traffic signs into smaller group. With the knowledge-based analysis, some

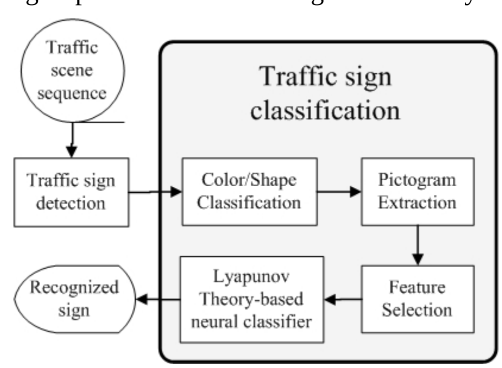


Figure 1. Block diagram of the proposed traffic sign recognition.

traffic signs can easily be recognized due to its appearance uniqueness. As the large database is branched and categorized, color and shape features are not longer required in the process. These features are redundant within the intra color-shape class and they contribute to the poor performance of recognition because of the illumination and rotation. Therefore, pictogram is further extracted with a proposed thresholding technique from the sign before passing to neural network. Due to the redundancy information of high dimensional input data feeding into neural network, the pictogram dimension of each traffic sign is reduced by extracting the salient features using Principle Component Analysis (PCA) and Fisher's Linear Discriminant (FLD), and subsequently the expressive data are trained in the Lyapunov Theory-based neural classifiers.

The organization of this paper is as: Section II briefly discusses about the traffic sign detection while Section III explains the proposed traffic sign classification. Simulation results and comparison are shown in Section VI and followed by conclusion and future works.

II. Traffic Sign Detection

Traffic signs are important to remind a driver of the current road situation. As demonstrated in Fig. 2, 100 classes of traffic signs can often be found in Malaysia. The iconic traffic signs are acquired from the Malaysia's Highway Code Test booklet**.** They are designed in the standard geometrical shapes such as triangle, circle, octagon, rectangle, square or diamond. The colors that used for traffic signs are yellow, blue, red, orange, black and white which is significantly distinguishable from the natural scene. The message of warning, prohibition, guidance, construction and maintenance are represented by the specific color and shape as depicted in Table I. They may contain a pictogram, a string of characters or both.

Traffic sign detection plays a vital role in the pre-processing stage of an intelligent vision-based TSR system to detect a possible traffic sign region out from complex road scenery. Apparently, the color of traffic sign is a salient

Figure 2. Malaysian traffic sign samples.

TABLE I
MALAYSIAN TRAFFIC SIGN CLASSIFICATION IN SHAPE AND COLOR.

Shape / Color	Diamond	Triangle downward	Square/ Rectangle	Circle	Octagon
Blue	--	--	Information	Obligation	--
Red	--	Yield sign	--	Prohibition	Stop sign
Yellow	Warning	--	Warning	--	--
Orange			Construction		
White	--	--	--	Speed limit	--

clue to attract the attention of a driver about the surrounding road conditions. Inspired by this unique feature, color segmentation techniques have been developed recently [4, 5, 8] for traffic sign detection due to the advantages of fast processing speed and relatively good performance. In this context, assuming that the input of road image has *r*, *g*, and *b* values for the normalized red, green and blue channels respectively. Hence, five newly color map are constructed based on the expressions (1)-(5) denoted in [9, 10].

$$R' = r - (g+b)/2 \tag{1}$$

$$G' = g - (r+b)/2 \tag{2}$$

$$B' = b - (r+g)/2 \tag{3}$$

$$Y' = (r+g)/2 - |r-g|/2 - b \tag{4}$$

$$W' = (|r-g| + |g-b| + |b-r|)/T_1 \tag{5}$$

The symbol *R'G'B'Y'* represent the red, green, blue and yellow color maps. The *W'* having values less than 1 depicts achromatic colors and *W'* of greater than 1 represents chromatic colors. T_1 is a threshold to extract the chromatic /achromatic color. The dominant colors of traffic sign will be highly discriminated from the background scene as displayed in Fig. 3. These color maps in Fig 3(c)-(f) are then transformed to binary images using color thresholding. The thresholding values are computed by averaging the positive pixels for individual map. An AND operation is applied on the color maps and the chromatic map to obtain the accurate thresholding map. Subsequently, morphological operations are performed on the binary image in order to erode unwanted pixels as well as to dilate the ROIs. Within the ROIs, the extracted region is verified as a traffic sign if it

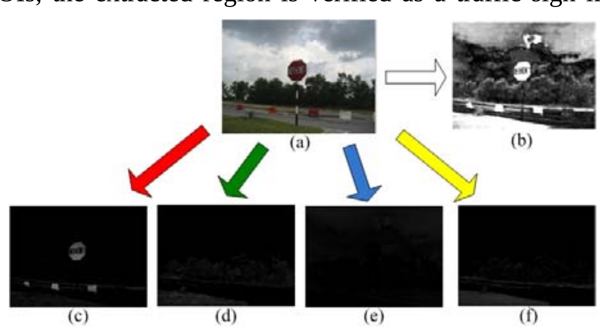


Figure 3. Color segmentation is applied to the (a) input image, to obtain (b) chromaticity, (c) red, (d) green, (e) blue, and (f) yellow color maps.

contains a certain amount of white or black pixels of pictogram and the symmetries. All shapes obtain symmetrical axes in both horizontal and vertical directions except for the triangle pointing downward.

III. TRAFFIC SIGN CLASSIFICATION

Once traffic signs are detected, they are passed to the classification to quickly recognize and obtain the particular functionality of each sign. In this section, a new recognition technique combining of color/shape classification, pictogram extraction, feature selection methods and Lyapunov theory-based RBF neural classifier is presented. Traffic signs are first branched into smaller subclasses based on its color and shape histograms [9]. The pictogram is therefore extracted and turned into binary image by discarding other unnecessary information. Feature extractions such as PCA and FLD are then applied to reduce the dimensionality before feeding into Lyapunov theory-based RBFNN [10].

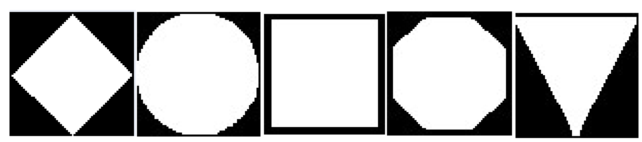
A. Color Histogram & Shape Classification

Color is an important element for traffic sign classification. Some road signs can be easily recognized regarding on its color uniqueness. The Malaysian traffic signs database denoted in Fig. 2 can be divided into subclasses based on the color histogram classification. Four color bins are created, i.e yellow/orange, red, blue, and black/white. Eventually, the traffic sign is assigned to the specific color bin where it holds the maximum value of pixel numbers. As illustrated in Fig. 4, traffic sign *#1*, *#2* and *#3* can be recognized under color histogram classification. The traffic sign *#1* has the highest red components and followed by blue color. On the other hand, the traffic sign *#2* has the highest blue color pixels and contains the red components as well. Sign *#3* is a black and white sign.

Besides color, traffic sign can be recognized with geometrical information. Therefore, shape classification is applied to the recognition system to further split the large traffic sign classes into smaller groups. Instead of detecting shape using Hough Transform, the application of template matching on shape detection may achieve better performance in real-time implementation. The templates depicted in Fig. 5 are masked with the segmentation regions, producing the masked regions. To calculate the best fit of the masked region to every template, two ratios are obtained, i.e.:

1. The total area of masked region over the total area of shape template,
2. The total area of masked region over the total area of the segmented region.

The purpose of having two ratios is that, to avoid the inaccuracy of template matching caused by the varying size of traffic signs. The relatively small or big segmented signs may affect the matching results. Therefore, by summing up the two ratios, the template that obtains the highest summation value is selected as the detected shape. In Fig. 4, the shape classification is performed on red, blue and yellow color bins. In yellow classes, the arrow sign *#4* and *#5* can be differentiated. In red color images, circle, triangle and polygon are separated. Hence, the sign *#6* and sign *#7* are easily recognized after the shape classification.



(a) (b) (c) (d) (e)

Figure 5. Shape templates in *32×32* dimension: (a) diamond, (b) round, (c) square/ rectangle, (d) octagon and (e) triangle downward.

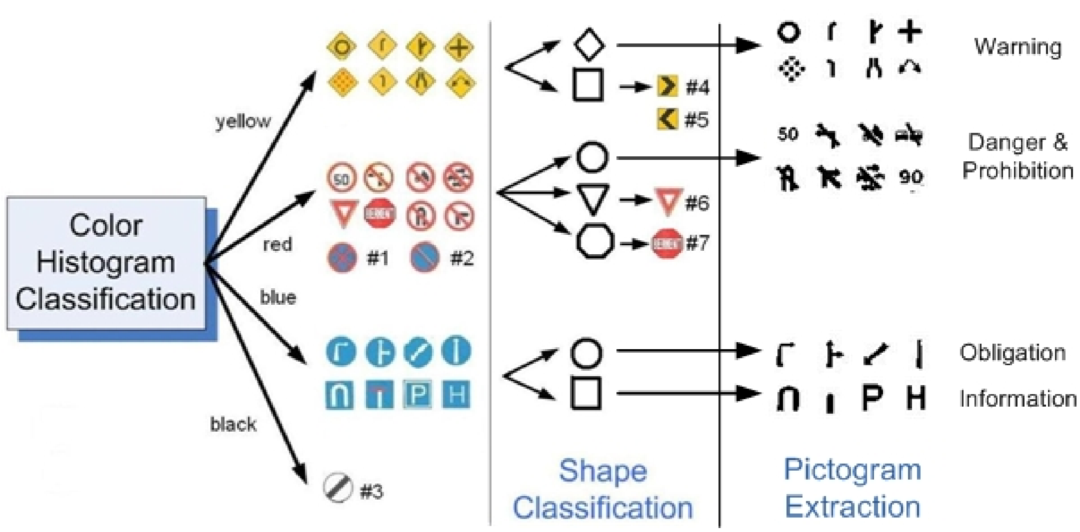


Figure 4. Color histogram, shape classification and pictogram extraction.

B. Pictogram Extraction

After the color/shape classification, the pictogram is extracted within the region of interest of each class. This stage is to remove the outer shape and color pixel since they are not longer required in the process. It may get rid of minor rotation of the shape and color illumination, which may affect the results of recognition. During the process, two cases of pictogram extraction are performed to ensure the removal accuracy. The first method is to stretch the pixel contrast of darkest and brightest pixels in order to have a great distinguishable contrast between the pictogram and background. A threshold is then applied to transform the pictogram into binary image. The second method is computed with a color pixel histogram. Gaussian filter is therefore applied to smoothen out of the graph curve. Local peaks are selected and only the first three peaks are used for the pixel extraction. These two cases are selected based on a ratio of the extracted region. If the ratio of the extracted pixels over the total region is less than a T_2, the first case is selected; or else the second case is taken to filter the sign of region except the pictogram.

C. Features Selection

Features selection is used to further reduce the input dimensionality and extract the salient representation of each signs. In this section, two features selections methods are discussed, i.e. PCA and FLD.

1) Principal Component Analysis (PCA)

PCA is applied to reduce the high dimensional traffic sign data and generate the most significant features to represent the pattern of a traffic sign. Given that the original image of two-dimensional matrix has been converted to a column vector M_i. A set of training traffic sign images, denoted as $\mathbf{M} = [M_1, M_2, ..., M_n]$ are employed to calculate the covariance matrix with the expression below [9]:

$$\mathbf{\Phi} = \frac{1}{n}\sum_{i=1}^{n}(M_i - \overline{M})(M_i - \overline{M})^T \tag{6}$$

where $\overline{M}$ is the mean image of training data. Eigenvalues and eigenvectors of the covariance Φ are calculated and recorded. Therefore, the vector $\mathbf{M}$ is transformed into the eigen-space as below:

$$\mathbf{B} = \mathbf{U}^T\mathbf{M} \tag{7}$$

where $\mathbf{U} = [U_1, U_2, ..., U_n]$ is the PCA projecting vector.

2) Fisher's Linear Discriminant (FLD)

The FLD is employed to obtain the most discriminant feature of traffic signs. It is used to calculate a linear projection of the set of training samples in the PCA eigen-space $\mathbf{B} = [B_1, B_2, ..., B_n]$ to obtain an optimal low-dimensional subspace in which the ratio of the between-class scatter and the within-class scatter (8) is maximized [8, 9].

$$\arg\left\{\max \frac{\mathbf{E}^T\mathbf{S}_B\mathbf{E}}{\mathbf{E}^T\mathbf{S}_W\mathbf{E}}\right\} \tag{8}$$

where $\mathbf{S}_b$ and $\mathbf{S}_w$ are the between-class scatter and within-class scatter respectively. The discriminating feature vectors $\mathbf{P}$ projected from the PCA to the optimal subspace can be calculated as follows:

$$\mathbf{P} = \mathbf{E}_{optimal}^T\mathbf{B} \tag{9}$$

where $\mathbf{E}_{optimal}$ is the FLD optimal projection matrix. These FLD features are then passed to the Lyapunov theory-based RBFNN as the network inputs for classification.

D. Lyapunov Theory-based RBFNN

RBF neural classifier is used to classify the traffic signs for each subclass after pictogram extraction. The basic structure of three layers RBFNN is shown in Fig. 6, where the first layer is the input layer, the second layer is the RBF nodes layer and the third layer is the output layer. The number of input neurons is the size of traffic sign features extracted by FLD while the number of output neurons is assigned to the number of task to be recognized. Let the first layer of input vector, $\mathbf{X}^{(1)}$ is assigned to be the FLD features $\mathbf{P} \in \Re^n$, where $\mathbf{P} = [p_1, p_2, \cdots, p_n]^T$. The RBF centers are denoted as $C_j \in \Re^n (1 \le j \le u)$. Each RBF unit is defined as:

$$X_j^{(2)} = \exp\left[-\frac{\left\|\mathbf{X}^{(1)} - C_j\right\|^2}{\sigma_j^2}\right], j = 1, 2, \cdots, u \tag{12}$$

where ||·|| indicates the Euclidean norm on the input space

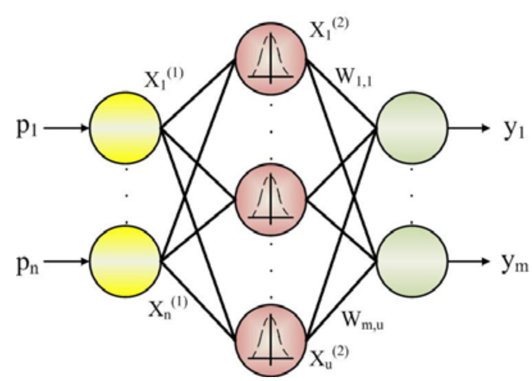


Figure 6. The RBF network structure.

while σ_j is the Gaussian width of the *j-th* RBF unit. After the application of RBF on input data, they are led to a linear weight linkage mapping from *u-th* RBF nodes to the *r-th* output y_r , where each output node has the relationship below:

$$y_r = \sum_{j=1}^{u} X_j^{(2)} w_{r,j} \; , r = 1,2 \cdots m \tag{13}$$

where $X_j^{(2)}$ is the input to the output node and $w_{r,j}$ is the system weights. To obtain a set of optimal system weights for traffic sign classification, a novel network training scheme is proposed based on the Lyapunov stability theory.

The idea of the Lyapunov Theory-based RBF filter has been first developed in [11] for adaptive filtering. The Lyapunov function of the network error between target outputs and network outputs are first defined. The weights are then adjusted based on the Lyapunov stability theory, so that errors can asymptotically converge to zero. Moreover, the selected Lyapunov function has a unique global minimum in the state space. By properly choosing the weight update law in Lyapunov sense, RBF outputs can asymptotically converge to the target outputs. In this section, the design in [11] is adopted and modified to apply the Lyapunov Theory-based RBF neural classifier for traffic sign recognition. The Lyapunov function is chosen as $V(k) = e_r^2(k)$, where $e_r(k)$ is the posterior error. The $V(k)$ is well selected based on the Lyapunov stability theory. For the given desired response $d_r(k)$, the weights update rules based on Lyapunov stability theory are denoted as below [12]:

$$\mathbf{w}_r(k) = \mathbf{w}_r(k-1) + \mathbf{g}_r(k)\alpha_r(k) \tag{14}$$

$$\mathbf{g}_r(k) = \frac{\mathbf{X}^{(2)}(k)}{\lambda_1 + \left\|\mathbf{X}^{(2)}(k)\right\|^2}\left[1 - \kappa \frac{|e_r(k-1)|}{\lambda_2 + |\alpha_r(k)|}\right] \tag{15}$$

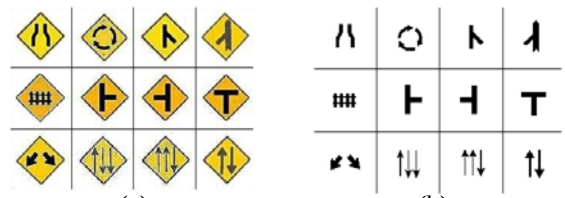
where the estimation of priori error $\alpha_r(k)$ is defined as follows:

$$\alpha_r(k) = d_r(k) - \mathbf{w}_r^T(k-1)\mathbf{X}(k) \tag{16}$$

where $0 \le \kappa < 1$. In order to prevent the singularities in the gain $g_r(k)$, small positive integers, λ_1 and λ_2 are added to the gain numerator. The theoretical design of Lyapunov theory-based RBF neural system is provided in [12].

IV. SIMULATION RESULTS

All simulation results were generated using Matlab 2009b with the Core 2 Duo processor at 1.8GHz with 1GB RAM. To evaluate the performance of proposed recognition system, two types of traffic sign data were prepared; i.e. color sign representation and binary pictogram representation as shown in Fig. 7. Each type of data representation contained training and testing set of samples. In the training set, each class composed of five training signs, in which they were perfect situation of iconic signs and real signs resulted from the detection. In the testing set, the images partially included real traffic signs, perfect signs with additional Gaussian noise and blur effect. In total, there were 100 classes of signs to be recognized. Of all there were 55 yellow signs, 28 red signs, 16 blue signs and 1 black/white sign. All traffic sign images were in the dimension of 32 by 32.



(a) (b)

Figure 7. Intra color/shape class samples in (a) set 1: color sign representation, (b) set 2: binary pictogram representation.

In this section, yellow traffic signs were used to investigate the performance of the proposed system. The performance was compared between data set 1 and data set 2. The training samples were used to train with the RBFNN while the testing samples were used to further evaluate the recognition rate. As demonstrated in Fig. 8, the recognition rate was plotted along the increment of PCA features. In the curve, the recognition rate increased proportional to the number of PCA features. However, data set 2 obtained higher training and testing recognition rate compared to the data set 1. This phenomenon showed that the extraction of pictogram removed most of the redundant information and it eased the training process of neural classifier. The PCA value was picked as 180 features in this stage for further evaluation.

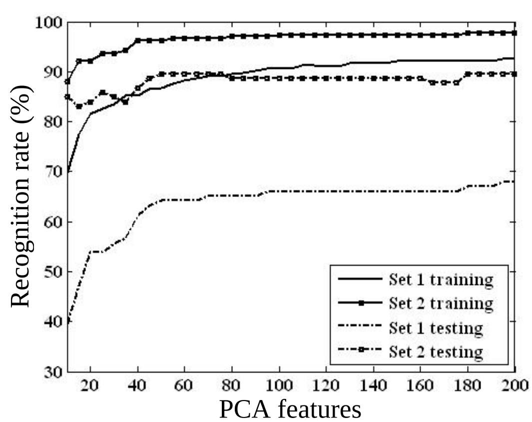


Figure 8. PCA features vs Recognition rate for warning signs.

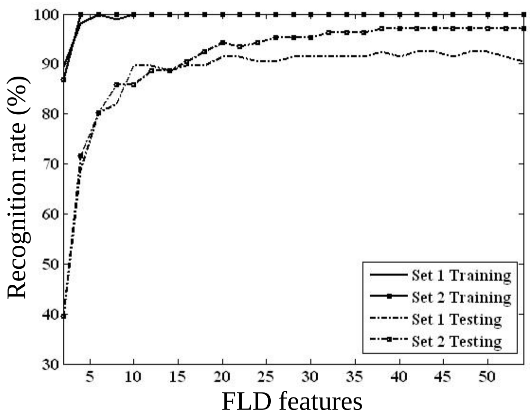


Figure 9. FLD features vs Recognition rate for warning signs.

During the training process, data set 2 achieved 100% of recognition rate faster than the data set 1 as plotted in Fig. 9. The recognition rate for both testing data increased accordingly as the number of FLD features increased. Nevertheless, the binary pictogram representation data type achieved higher recognition rate as shown in Table II due to some of the following reasons:

1) Pictogram which was the important information for the road user contained only 10~20 % of the entire sign. But, 80% of the background pixels confused the neural classifier doing the recognition job. Therefore, it was significant to remove the outer shape and color pixels after the color/shape classification.

2) Invariant to shape geometry since minor rotation of the shape from far to near field did not make a big change for the pictogram.

3) Color inconsistency may contribute to the low performance of neural classifier. In the proposed system, the pictogram was transformed into binary form which did not affected by the illumination.

4) It may contribute to fast training process due to less redundant information.

TABLE II
CLASSIFICATION RESULTS FOR DIFFERENT SIGN REPRESENTATION

Representation	PCA Feature	LDA Feature	Recognition rate
Set 1	180	40	92.453
Set 2	180	40	97.169

TABLE III
OVERALL PERFORMANCE OF THE PROPOSED TRAFFIC SIGN CLASSIFICATION.

Group	Training Images	Testing images	PCA Feature	LDA Feature	Recognition rate (%)
Warning	275	110	180	40	97.169
Prohibition	140	56	95	22	91.667
Obligation	55	22	50	9	100
Information	25	10	15	4	100

Overall performance of the entire database was shown in Table III. As can be seen, the proposed recognition system would give 97% of recognition rate for the warning sign while the prohibition group could achieve 92% of recognition rate. For obligation and information group, they were smaller size in group. They could achieve 100% recognition rate with or without the pictogram extraction due to less complexity.

V. CONCLUSION

A new traffic sign recognition system composing of color/shape classification, pictogram extraction, feature selection and Lyapunov theory based RBF neural classifier has been presented in this paper. The recognition rate is further improved by extracting the traffic sign pictogram from the color/shape classification. This is because the color and shape information has been analyzed beforehand and it is not required anymore in the classification stage. The removal of shape and color has led to the less confusion of information for the neural classifier. Experimental results have shown better performance of the proposed recognition system.

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