Automatic Detection and Recognition of Traffic Signs

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***Abstract*—Automatic detection of road sign is a challenging but demanding job. A new approach namely automatic detection and recognition of traffic signs (ADRTS) considering color segmentation, moment invariants, and neural networks has been proposed in this paper. Experimental result proves the superior performance in the detection and recognition of road signs. Computational time complexity is also quite low that makes it applicable for the real time system.**

***Index Terms*—traffic sign, automation, neural network, moment invariants, hu moment.**

I. Introduction

Each government imposes some sets of rules and regulations to ensure a safe traffic system. Each person specially the vehicle driver must obey these rules and regulations for a secure travel. Some of those laws are represented as visual language such as different signs and texts that are known as traffic signs. There are various categories of traffic signs that we can see beside the roads. An efficient driver must notice each of the road signs in front of him and need to act accordingly. Otherwise disastrous things can happen. A driver may not notice each of the road signs in front of his car due to lack of care or human perception errors. Therefore, it is desirable of having a automatic road sign detection and recognition system to assist the driver to ensure a safe travel [1].

Numerous research works have been conducted for automatic detection and recognition of road signs in order to assist the driver. Still more research works are being conducted on the issue because of its enormous potential in practical traffic control system applications. Generally, road sign detection and recognition is divided into three stages: detection, classification and recognition. Detection stage is responsible for identifying region of interest (ROI) from the picture frame that is taken by a video camera mounted on top of a vehicle. ROI is the most likely part of the image that may contain traffic signs. The second stage of automatic detection and recognition of road sign is the classification stage. In this stage each ROI is classified according to there shape and color. In the last stage individual road sign is recognized from its class.

Many techniques are used in the literature for extracting the ROI's. Among these color segmentation is widely used for its simplicity and good segmentation performance. There exists various color spaces, such as RGB (Red, Blue, Green), HS(L/V/I) (Hue, Saturation, Lightness/Value/Intensity), YUV (Luminance - Chrominance) etc. Different authors used different color spaces for image segmentation. Paulo et. al. [2] used HSV color space. They converted the RGB image into the HSV because it decouples the color and intensity information. Red and Blue components are identified by analyzing the H and S components. They devised an equation that takes the H and S components of a pixel as input to identify whether it is in the Red or Blue region. Fleyeh described three methods for color detection and segmentation [1] . Instead of using HSV color space Fleyeh used improved HLS (IHLS) [3] color space. He converted the images from RGB color space into IHLS color space. IHLS color space is similar to HLS color space. It is specially designed for image processing rather than computer graphics. Another important property of this color space is its independence between the chromatic and achromatic components [4]. In [5], [6] Fleyeh introduced a new technique named shadow and highlight invariant for color segmentation of the traffic signs. Broggi et. al. [7] presented two methods for color segmentation using YUV and RGB color spaces. Though RGB color space is highly depended on the brightness, many authors [7]–[9] prefer RGB color space due to its no need of color space conversion. Broggi et. al. [7] described a technique named chromatic equalization that subsides the problem of RGB color space. Hsu et. al. [10] used template matching technique along with the HSI color segmentation technique. Vitabile et. al. [11] preprocess the image by reducing noise using a non-linear smoothing filter. They used HSV color space rather than RGB color space. They devised a dynamic pixel aggregation technique using a dynamic non-linear threshold for road sign detection.

Different authors used different techniques in classification stage. Paulo et. al. [2] classified the detected ROI's in different traffic sign categories using color and shape information. Different authors used different shape classification algorithms

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[12], [13] to classify the shapes in the ROI's as circular, square and triangular. Cyganek [14], [15] exploited neural classifier to identify the circular shape traffic signs using moment invariant as the feature. Fleyeh et. al. [6] used Fuzzy ARTMAP classifier to classify the road signs in different classes using Zernike moments as the feature. Broggi et. al. [7] used the pattern matching technique to identify shape of the ROI. Vitabile et. al. [11] did the shape classification using a similarity coefficient between a segmented region and the representing set of images for each road sign shape. Escalera et. al. [8] chose the corners of the shape of a road sign as the feature to identify it. A template matching technique is used in [9] to classify road signs.

Before the recognition stage road signs are detected and classified according to their shape and color information. In the recognition stage individual road sign is recognized from its class. Many techniques are used in the literature for this purpose. Among them most popular technique is neural network classification technique. Different authors used different information, such as average value of R, G and B of a RGB image [11], gradient factors, angular radial transform, affine moment [15], of the segmented image as the feature set to recognize individual road sign. The whole segmented image was also used as the feature for neural classifier [8]. Pattern or template matching technique is used in [2], [7], [9].

In this paper, we have proposed a new algorithm for automatic road sign detection and recognition. We assume an image in front of the vehicle is taken by a mounted camera. Then this image is analyzed to detect and recognize road signs. We use the color segmentation algorithm to segment the road sign from the image. In the color segmentation algorithm, we use RGB color space because of its acceptable performance and no need of color space conversion. Our color segmentation algorithm demonstrates considerably good performance in both ideal and non-ideal illumination conditions at different times of the day and night. The segmented road sign is then classified according to their color and shape. We use Hu moment invariants as the feature set and neural network classifier to classify road signs to their respective classes. Finally, individual road sign from its class is recognized using another neural network classifier. We have performed a large number experiments on more than one hundred images. The experimental results showed the superior performance of our new algorithm and its effectiveness in real time.

The rest of the paper is organized as follows: a brief description of the Bangladeshi road signs is presented in Section II, while the supporting literatures that are used directly in our proposed model are described in Section III. Our proposed model is illustrate in Section IV. The experimental results are described in Section V and finally some concluding remarks are provided in Section VI.

II. Bangladeshi Road Signs

The mandatory and warning traffic signs in Bangladesh are shown in Figure 1 and 2. Those signs can be found in http://www.brta.gov.bd/traffic.php. From those figures we

Fig. 1. Some of the Mandatory traffic signs in Bangladesh

Fig. 2. Some of the warning traffic signs in Bangladesh

can primarily categorize the traffic signs into two categories according to the color. One of them is red signs and the other one is blue signs. Then red road signs are categorized into four categories: circular, triangular, circular with straight line and other. Stop and no stop sings fall into other category. Blue road signs are categorized into two categories: circular and rectangular. Each category of road sign will be handled separately during both detection and recognition stages.

III. Supporting Literatures

In this Section, we describe related research works those are directly used in our new automatic road sign detection and recognition algorithm.

A. Color Segmentation

Benalla et. al. [16] proposed the following color segmentation algorithm for segmenting Red, Blue and Green regions in the image.

FOR all pixels i in image
 IF $R_i > G_i \&\& R_i - Gi > \Delta_{RG}; R_i - B_i > \Delta_{RB}$
  THEN pixel i is RED
 ELSE IF $G_i > R_i \&\& G_i - R_i > \Delta_{GR}; G_i - B_i > \Delta_{GB}$
  THEN pixel i is GREEN
 ELSE IF $B_i > G_i \&\& B_i - G_i > \Delta_{BG}; B_i - R_i > \Delta_{BR}$
  THEN pixel i is BLUE
 ELSE pixel i is WHITE (or BLACK)
 ENDIF
ENDFOR

Their algorithm performs well enough for segmenting road signs in ideal illumination condition. But in case of non-ideal illumination conditions at different times of the day, the performance of their algorithm becomes relatively poor. They chose fixed values for the thresholds Δ_{RG}, Δ_{RB} and Δ_{GB}. This is the main reason for which their algorithm performs poor in non-ideal illumination conditions. If the values of the thresholds Δ_{RG}, Δ_{RB} and Δ_{GB} were chosen adaptively for different non-ideal illumination conditions segmentation performance can be improved.

B. Hu's Moment Invariants

Moments invariants have become the classical tools for object recognition. They are one of the most important and most frequently used shape descriptors. Though they suffer from some intrinsic limitations (the most important of which is their globality, which prevents them from being used for recognition of occluded objects), they frequently serve as a reference method for evaluation of the performance of other shape descriptors [17].

Two-dimensional moments of a digitally sampled $M \times N$ image that has gray function $I(x,y), (x = 0, ..., M-1, y = 0, ..., N-1)$ is given as [18],

$$m_{pq} = \sum_{x=0}^{x=M-1} \sum_{y=0}^{y=N-1} (x)^p (y)^q I(x,y) \tag{1}$$

$p, q = 0, 1, 2, ...$

The moments $f(x,y)$ translated by an amount (a,b), are defined as,

$$\mu_{pq} = \sum_{x=0}^{x=M-1} \sum_{y=0}^{y=N-1} (x-a)^p (y-b)^q I(x,y) \tag{2}$$

Then central moment μ_{pq} can be calculated from equation 2 by substituting $a = \overline{x}$ and $b = \overline{y}$. Where

$$\begin{aligned} \overline{x} &= \frac{\sum_x \sum_y xI(x,y)}{\sum_x \sum_y I(x,y)} \\ \overline{y} &= \frac{\sum_x \sum_y yI(x,y)}{\sum_x \sum_y I(x,y)} \end{aligned} \tag{3}$$

$$\mu_{pq} = \sum_x \sum_y (x-\overline{x})^p (y-\overline{y})^q I(x,y) \tag{4}$$

We get the normalized moment η_{pq} by applying a scaling normalization to the centralized moment in equation 4.

$$\eta_{pq} = \frac{\sum_x \sum_y (x-\overline{x})^p (y-\overline{y})^q I(x,y)}{\left(\sum_x \sum_y I(x,y)\right)^{\frac{p+q+2}{2}}} \tag{5}$$

Invariants to translation and scaling are trivial since central and normalized moments are invariant to translation and scaling. Invariants to rotation was first introduced by Hu in 1962 [19], who employed the results of the theory of algebraic invariants and derived his seven famous invariants to in-plane rotation of 2-D objects. Those seven invariants are given in [19]. The Hus invariants, despite of their drawbacks, became classical and found numerous successful applications in various areas.

IV. Proposed Model

In our proposed road sign detection and recognition algorithm we also use detection, classification, and recognition stages.

A. Road Sign Detection

Bangladeshi road signs have predefined colors and shapes. The colors are Red, Blue, and Yellow and the shapes are circular, triangular and rectangular. For this reason, rather than using generalized object segmentation algorithms, we prefer color segmentation algorithm to detect road sign or to find the ROI. We use RGB color space for our color segmentation algorithm because of its simplicity and no need of color space conversion.

We use a modified version of the color segmentation algorithm of Benallal et. al. [16] discussed in Section III-A. Benallal et. al. kept the color thresholds Δ_{GR}, Δ_{GB} and Δ_{RB} constant for different non-ideal illumination conditions throughout the whole day and night. We observed that it is efficient to use different adaptive color threshold values for different non-ideal illumination conditions at different times in the day and night. Therefore, we need an adaptive method to determine the threshold values. We adapt the threshold values based on the intensity or brightness of the time. We infer the current intensity by the following equation:

$$I = \frac{R+G+B}{3}$$

We set the threshold values based on the observed intensity. We adapt the threshold values periodically with an apposite period because intensity does not vary frequently.

To find out the region of interest (ROI), that may contain the different categories of road signs, we first segment the input image using Red color. After this process we get a binary image containing a large number of regions representing the Red regions in the original image. Among these regions we consider only the largest three regions as our candidate ROI. This is because the three largest regions are most likely to be road signs. If the input image contains any road sign of red color then a ROI will be found containing that road sign. We may get a ROI that have red color but not a road sign. This may happen when the image, taken by the camera, contains other objects with red color. Next, the image is segmented using the blue color and we get some ROI's that may contain blue road signs. These road signs will be classified in the following stage and any false ROI will be rejected.

B. Road Sign Classification

The output of the previous stage is some ROI's. These ROI's are essentially the binary images of the road signs that contain Red or Blue color. These binary images only represent the outer shapes of the road signs without the inside figures; because none of the inside figures contain any Red or Blue pixel. In this step, each of the ROI's shape and color will be analyzed to classify into their respective classes. In the best case, an ROI may contain only the shape of the road sign and this is very trivial to handle. In the average case, an ROI may contain some noise binary objects around the shape of the road sign. In this case, we assume that the area of a noise object is less than the area of the shape of the road sign. Using this assumption the noise objects are excluded from the ROIs. In the worst case, the area of the noise object will be higher than the area of the shape of the road sign and the road sign would be classified inaccurately.

Each type of road signs, Red and Blue, is treated separately. A neural network classifier is used in this purpose. We use Hu moment invariants as the feature set for classification. There are four types of shapes of Red road signs detailed in Section II. We captured over one hundred images by a camera. Then the binary images of the shapes of the road signs are extracted from the captured images as discussed earlier in this Section. Seven Hu moment invariants also calculated from these extracted shapes. A neural network is trained by those values. Using this trained neural network Red road signs are classified into four classes, such as circular, triangular, circular with cross and others. Similarly, another neural network is trained in for the Blue road signs. Blue road signs are classified into only two classes, circular and triangular, using this neural network. ROI's which do not contain a road sign will be rejected in this stage.

C. Road Sign Recognition

After observing the Bangladeshi road signs from Figure 1 and 2, we conclude that triangular red road signs contain only black figure against white boundary. These figures can be easily extracted considering the black pixels only. Among the circular road signs only the speed limit signs do not have a straight cross in the middle. These speed limit signs contain numbers against white background that can be extracted easily. Rest of the circular road signs contain straight cross or straight line against white or blue background. Some of them have a figure behind the straight line or cross, which can be extracted easily. Few circular road signs have only blue color with white arrow sign inside. All rectangular road signs have only blue color with white arrow sign inside. Those arrows from the rectangular or circular road signs can be extracted easily by considering the white pixels from the binary image of ROI.

Each of the classes will be handled separately in this stage. A neural network will be used to recognize inside figures for each of the classes. Hu moment invariants are extracted from the sample road sign images. Neural networks will be trained by the extracted Hu moment invariants. The speed limit road signs are dealt with a special care since they contain the speed limit in the form of numerical digits and we need to determine the numerical value from these digits. Each of the digits are extracted separately and they are recognized by a trained neural network. After determining their decimal place the actual numerical value of the road sign is calculated.

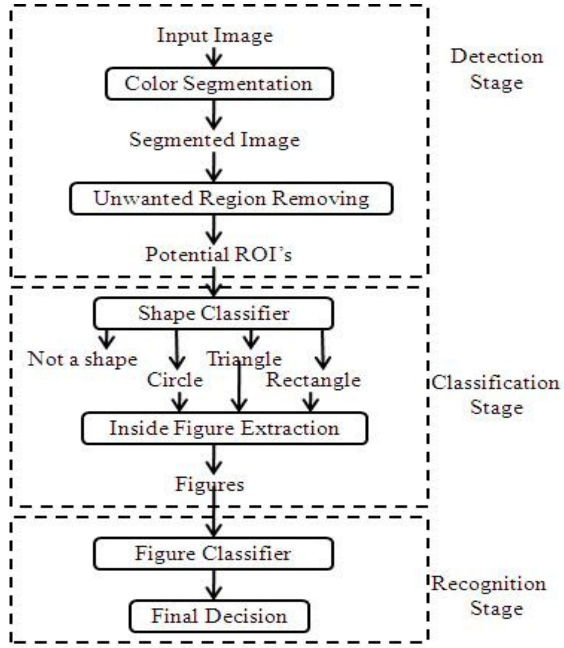


Fig. 3. Overview of the proposed model

The overall view of our proposed model is illustrated in Figure 3.

D. Neural Network (NN) Classifier

A neural network is a mathematical or computational model that tries to simulate the structure or functional aspects of biological neural networks. It consists of an interconnected group of artificial neurons and processes information using a connectionist approach to computation. In most cases, a NN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase. The tasks of the neural networks are pattern recognition or classification, regression, clustering, estimation, sequential decision making etc. The applications of neural network spread from different businesses to scientific applications.

As we discussed in the previous sections, we develop different neural networks in different stages because one neural network would make it more complex. Such as, we develop a NN classifier to classify red road signs into different shapes such as circular, triangular and others. Then we develop a NN classifier for each of the shapes to recognize road signs from the group. Each of the neural networks have seven neurons in the input layer. This is because, we select seven hu moment invariants as the feature set. These seven hu moment invariants are calculated from the subject images. There are two hidden layers in each of the neural networks. Each hidden layer comprises six and four neurons respectively. The number of neurons in the output layer depends on the number of classes. For example, in the first neural network we have four neurons in the output layer for four classes of red road signs.

We use feed forward neural networks and we train each of the neural networks using Levenberg-Marquardt backpropagation algorithm. This is a supervised learning scheme and use mean squared error as a cost function. The main advantage of this algorithm is that its convergence time is very low and it uses small number of iterations. Figure 4 shows some of the signs used to train the neural networks. Hu moment invariants are calculated from the binary image of the signs and these values are used to train the networks.

Fig. 4. Some of the traffic signs are used to train the neural networks

V. Simulation and Results

We have conducted several experiments to verify the efficiency and the accuracy of our proposed model for the automatic detection and recognition of road signs. We implemented our proposed model in MatLab 7.2 and simulated the program for over one hundred and fifty images. Some of the experimental results are shown in Figure 5 and 6. Figure 5(a) shows a input image containing speed limit road sign. Figure 5(b) shows the detection of road signs. Figure 5(c) shows the color segmented binary image. Figure 5(d) shows the binary image of the shape after removing the unwanted regions. Figure 5(e) shows the binary image of the inside numbers. Figure 5(f) shows the separation of the digits. Figure 5(g) shows the final result. Figure 6(a) shows another input image containing a lot of red color regions. Figure 6(b) shows the color segmented binary image. Figure 6(c) shows the detection of potential ROI's. Figure 6(d), 6(e), 6(f) show the binary images of the potential ROI's. Figure 6(g) shows the inside figure. Figure 6(h) shows the rejection of ROI's as a traffic sign. Figure 6(i) concludes the final result.

The overall statistics are shown in Table I and II. In Table I, we observe that sign detection rate is quiet good in low illumination condition in the cloudy day or night. This has been resulted from using variable thresholds during color segmentation. The overall detection performance is 95%, which is quite good compared to some previous works [2] (94%), [6] (95%), [7], [10] (94%), [11] (92%). In Table II, we can see that the sign recognition rate is 93%, which is also very good relative to some previous works [2], [6], [7], [10], [11]. In our experiment, we also uses some input images which contain no road sign. Table III shows the result of that experiment. We observe that 11% images are falsely selected as potential road sign in the detection stage. However, only 3% of the images were falsely recognized as the road signs.

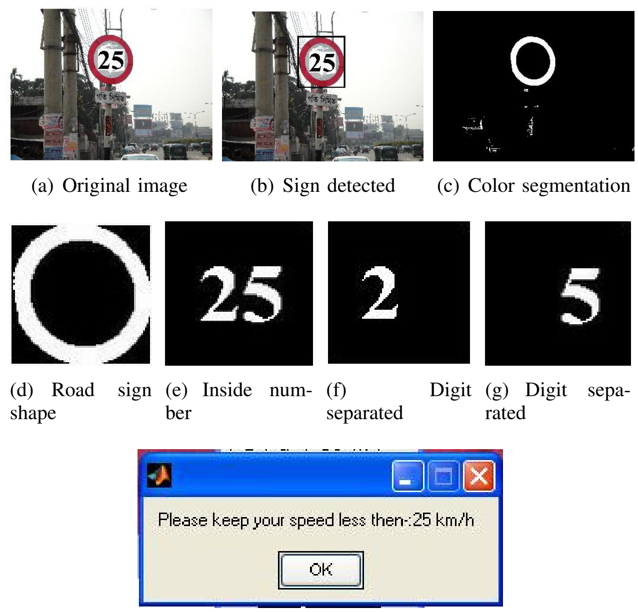
TABLE I

Road Sign Detection Statistics			
Illumination	Input Image	Sign Detected	Success Rate(%)
Low	25	23	92
Medium	95	93	98
High	56	51	91
Total	176	167	95

TABLE II

Road Sign Recognition Statistics				
Input Image	Image Detected	Image Recognized	Success Rate(%)	Overall Success(%)
176	167	164	98	93

This 3% false recognition rate is quite low. For an input image of resolution 4000×3000 it takes avg. $4s$ to produce the final decision in a laptop having 1GB RAM and 1.8GHz Intel dual core processor. As we decrease the resolution of the image running time also reduced dramatically. For an image of size 400×300 we also get the correct result and it takes less than $1s$ to produce the final result. Therefore, the time complexity of our proposed method is low enough to apply it in a real time system.



(a) Original image (b) Sign detected (c) Color segmentation

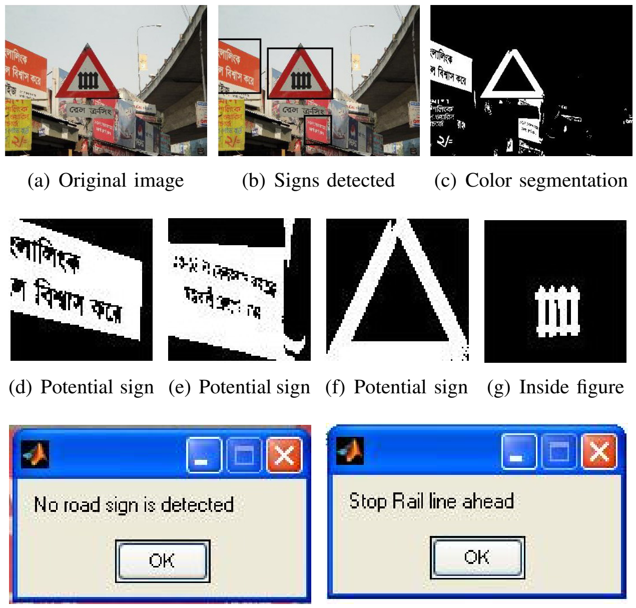
(d) Road sign shape (e) Inside number (f) Digit separated (g) Digit separated

(h) Final decision

Fig. 5. Simulation using speed limit traffic sign.

TABLE III

Road Sign False Detection Statistics				
Input Image	False Detection	False Recognition	False Det. Rate(%)	False Rec. Rate(%)
35	4	1	11	3



(a) Original image (b) Signs detected (c) Color segmentation

(d) Potential sign (e) Potential sign (f) Potential sign (g) Inside figure

(h) False sign rejected (i) Sign recognized

Fig. 6. Simulation show the rejection of false ROI

VI. Conclusion

In this paper, we described a new approach for automatic road sign detection and recognition in real time. We captured the images in front of the car by a camera. Then RGB color space is used to segment the traffic sign from the image. We used the Neural Network classifier in different stages to classify the different shapes and inside figures that leads us to the final decision. The experimental analysis showed the better performance our approach. We will conduct our research further to improve the robustness of this new approach so that it can perform better in all kinds of atmospheres and luminance conditions. In future, we will use machine learning approach so that our system can learn from the current environment and become dynamic.

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