A Fast Traffic Sign Detection and Classification System Based on Fusion of Colour and Morphological Information

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Abstract: *A new method for automatic classification of traffic signs is proposed in this paper. The proposed method is based on the fusion of colour and morphological information. The strategy consists of three steps. First, colour information in HSI colour space is used to segment the input image and finding the region of interests (ROIs) with red pixels. Then, morphological profile is building by employing opening and closing operators on each band of colour image. Next, statistical feature extraction is performed based on both morphological profile and original colour image. Finally, the feature vector is classified by support vector machines based on one-vs.-rest method. The proposed method was tested on domestic database including four classes of red signs. Experimental results show the hit-rate of about 97% in considerably low process time.*

Keywords: Data fusion, morphological profile, statistical features, traffic sign classification, support vector machines (SVMs).

1. Introduction

Automatic traffic sign detection and classification is an essential task for intelligent driver support systems (DSSs) that continuously monitor the driver, the vehicle, and the road. It informs the driver about upcoming decision points and traffic situations by recognizing the signs. The aim of DSS is to increase transportation efficiency and road safety.

Most of the DSSs are comprised of two modules, Detection and classification. In detection module image segmentation is performed to detect traffic sign from a road scene image. Then in classification module this traffic sign must be classified to one of the predefined traffic sign classes. But traffic sign detection and classification presents many challenges which make it a difficult task such as different seasons, different weather conditions e.g. sunny, foggy, rainy and snowy conditions. The system should be able to deal with all these constraints. Though there are well-known challenges for sign detection, road signs have well defined color, shape, size and position, which help in detection procedure.

Since 1980 that Japanese started the research on traffic sign detection [1], a wide range of techniques have been suggested for the detection and classification of road and traffic signs. We can categorize existing classification methods into two. The first category consists of techniques that use traffic signs appearance characteristics directly. For example in [2-4] color information is used for sign detection and shape information extraction is performed in [5-7]. In second category, first, a feature extraction is done and then classification is performed based on these feature vectors. Examples of features used in road-sign classification are moment invariants [8], Zernike Moment [9] and wavelets [10], [11]. Different classification methods such as various neural networks [3], [12] and SVM [2] are used to solve the problem of traffic sign detection.

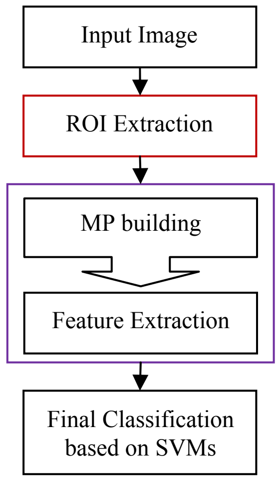

Figure 1. Algorithm description

In this paper, we propose a new automatic system for classification of traffic signs. The original contribution of this paper is fusion of morphological and colour information. The algorithm consists of three main steps (see Fig. 1). Initially we search the input image for candidate red colour regions, which named region of interests (ROIs). In this step the colour information is used in hue-saturation-intensity (HSI) colour space. In the second step, opening and closing operators are used to

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build morphological profile, and then statistical feature extraction is performed on each image of these profile. Finally in the third step, these extracted colour-morphology feature vector, is classified by support vector machines based on one-vs.-rest method. We use domestic database including four classes of red signs to evaluate the effectiveness of the proposed method. Experimental results show the accuracy achievement of about 97% in considerable low process time.

The rest of the paper is organized as follows. In Section 2 methodological framework of the proposed algorithm is reviewed. Experimental results are presented in Section 3. Finally, the proposed method is concluded and discussed in Section 4.

2. Methodological Framework

As shown in Fig. 1, the proposed algorithm includes the following parts: ROI extraction, MP building and then statistical feature extraction, and final classification based on SVMs.

2.1 Finding ROIs

The main task of this part is to segment the input image and extract out the regions that contain traffic sign. We use HSI colour space model to detect red regions because illumination conditions have less influence on this model than on the RGB model. We use the following criteria which obtained through trials and errors:

$$\begin{aligned} &0.02 < \text{Hue} < 0.9 \\ &0.1 < \text{Saturation} \\ &0.02 < \text{Intensity} \end{aligned} \tag{1}$$

The resulting image is then translated to a binary image with the pixels of interest being white and others black (see Fig. 2(c)). Final ROIs are regions that their areas satisfying the following criterion:

$$500 < \text{Area} < 5000 \tag{2}$$

As shown in Fig. 2(d), by taking into account the smallest rectangle containing the ROIs, from original image, ROIs are extracted. After removing background, all of rectangles are resized to 30×30 pixels.

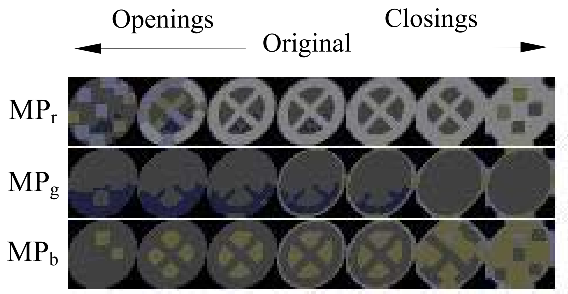


Figure 3. Morphological profiles for three color image bands. With three opening and closing, disc SEs with N=3.

2.2 Morphological Profiles

Opening and closing are two fundamental operators in mathematical morphology. These operators are applied to an image with a set of known shapes, called the structuring elements (SEs). For a given SE, opening or closing allows one to know the size or shape of some objects present in the image: The objects that are smaller than the SE are deleted, whereas the others (that are bigger than the SE) are preserved. To determine the shape or size of all elements present in an image, it is necessary to use a range of different SE sizes. This concept is called granulometry [13].

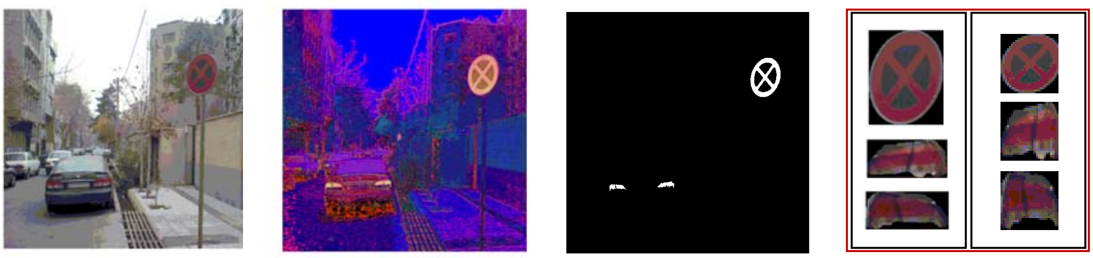
MPs are defined by using the granulometry. An MP is composed of the opening profile (OP) and the closing profile (CP) and the original image. As shown in Fig. 3, we can define an MP for each band of color image. Therefore MPs are building as follows:

$$MP = \{ MP_r , MP_g , MP_b \} \tag{3}$$

where

$$\begin{aligned} MP_r &= \{ OP_{rN} , \ldots , OP_{r1} , I_r , CP_{r1} , \ldots , CP_{rN} \} \\ MP_g &= \{ OP_{gN} , \ldots , OP_{g1} , I_g , CP_{g1} , \ldots , CP_{gN} \} \\ MP_b &= \{ OP_{bN} , \ldots , OP_{b1} , I_b , CP_{b1} , \ldots , CP_{bN} \} \end{aligned} \tag{4}$$

Here, I is the original image and N is the total number of opening or closing with a disc of size 1 with radius increment 1. We named N as MP factor and it can be determined empirically for best performance.



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

Figure 2. (a) original image, (b) HSI image, (c) ROIs in binary image and (d) extracted rectangles

2.3 Statistical Feature Extraction

In our approach instead of using traffic signs appearance characteristics directly, a small number of features are extracted from each image of MP. In this case, each image of MP is considered as a single grayscale image, and then some features are extracted from this image. In this paper we consider statistical features of a grayscale image. We select three features, mean, variance and entropy.

Let i be intensity value of grayscale image, then $P(i)$, the probability density function can be expressed as follows:

$$P(i) = \frac{n(i)}{M} \qquad 0 \le i < L-1 \tag{5}$$

where $n(i)$ is the number of pixels with intensity value of i, L denotes gray level of image, and M is the total number of image pixels that here is equal $30 \times 30 = 900$. By using (5), the following statistical measurements are extracted from each grayscale image of MP:

$$\begin{aligned} \mu &= \sum_{i=0}^{L-1} iP(i) \\ \sigma^2 &= \sum_{i=0}^{L-1} (i-\mu)^2 P(i) \\ En &= -\sum_{i=0}^{L-1} P(i)\log_2[P(i)] \end{aligned} \tag{6}$$

where μ, is statistical mean value σ^2, is variance and En is a scalar value representing the entropy of grayscale image.

Clearly, from each single image of MP, we would have a feature vector in dimension three. Thus a $3 \times 3 \times (2N+1)$ dimensional feature vector is extracted from MP. Comparatively to the methods like in [12] that not using any feature extraction algorithm, the dimension of feature vector is significantly low. For example by using the method introduced in [12], we would have a feature vector in dimension of $3 \times 30 \times 30$.

2.4 Final Classification Based on SVMs

The main task of the classification part is to classify the extracted ROIs presented to its input into the category they belongs to. Four categories of traffic signs were selected for recognition in this work (see Fig. 4). They are give way, no entry, stopping prohibited, and no parking. So we use four Support Vector Machine (SVM)-based classifiers. As shown in Fig. 5, one to one architecture is used because of expandability of the system. In this architecture, new type of traffic signs need only be trained individually without any effect on prior classifiers. There are only two possible outputs for each classifier the road sign either belongs to the particular class or does not. We used SVM classifier based on one-vs.-rest method and employing a linear kernel function for each SVM classifier. The total number of images used for training and testing of each class are mentioned in Table I. We used database include not only road-sign images, but also non-road-sign to enhance the rejection capability of the classifiers. It is important that each class specific classifier can reject a road sign that does not belong to its class, so for training, also other signs are used as incorrect patterns. As an example, for training a SVM classifier for no entry sign, we employed 15

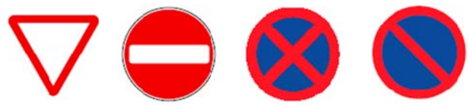


Figure 4. Selected categories of traffic signs

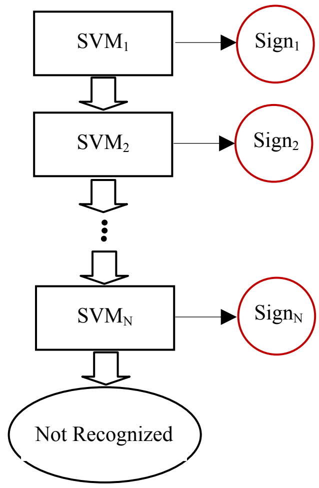


Figure 5. Classification based on one to one architecture

TABLE I: Classes, number of images, and class specific hit rates

Class		No. of Images		Hit	Miss	Hit Rate
No	Name	Training Images	Test Images			
1	Give way	9	9	9	0	100
2	No entry	15	15	13	2	86.67
3	Stopping prohibited	16	16	16	0	100
4	No parking	10	11	11	0	100
5	Non-sign	50	121	119	2	98.35
Total		100	172	168	4	**97.67**

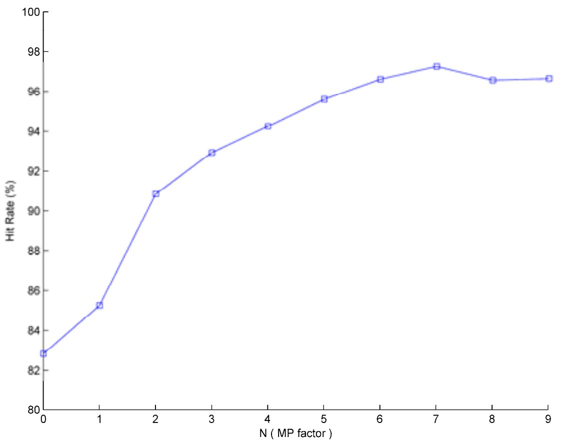


Figure. 6. Hit rates obtained by proposed method versus increment of MP factor N

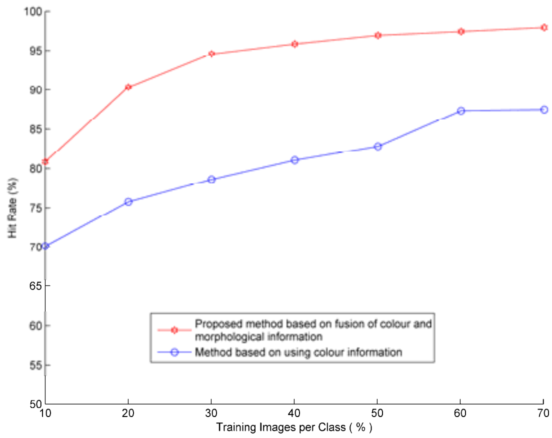


Figure. 7. Hit rates obtained by two methods versus percentage of the images for training

TABLE II: Comparison of three methods

Method	FV Dimension	Processing Time [ms]	Hit Rate
[12]	2700	1230	97.32
Colour based	9	720	82.80
Our approach	135	977	96.90

samples of this sign as correct patterns and also 85 samples of other classes as incorrect patterns.

3. Experimental Results

For evaluation the performance of proposed method, the system was tested on database including four classes of red signs. We collected the data set from different parts of Tehran city in different days and different times of a day. The images of this database are also containing red objects the same as the road signs. Table I shows the experimental results of our approach based on "leave one out" method. In this experiment, we choose N (MP factor) equal 7. Fig. 6 shows the effect of choosing different values for N. As mentioned before N can be determined empirically but we proposed the following constraint to choose the proper value for N:

$$(2N+1) \leq \frac{size(ROI)}{2} \qquad (7)$$

where, in this paper, *size*(*ROI*) is equal 30.

Fig. 7 demonstrates the results of the experiment that aimed to compare the impact of fusion of information. As shown in this figure, the proposed method that using fusion of colour and morphological information has comparatively better performance than the method based on using only colour information. This experiment was implemented for different numbers of images for training and for both methods feature extraction is performed based on section 2.3.

For intelligent driver support systems (DSS) the images are acquired by cameras mounted on a moving vehicle and need to be processed for online detection. Therefore the processing time for classification should be minimized. As shown in table II, feature vector dimension directly impact the processing time. In this table our approach has been compared with the method presented in [12] and the method that based on using only colour information. Compare to [12], our method despite considerably reducing in processing time, has given acceptable performance. Since the method presented in [12] has been used total pixels of ROIs in three colour bands as feature vector, the processing time of this method is higher, although has been demonstrated good performance.

4. Conclusion and Remarks

A new method for automatic classification of traffic signs was proposed. The contribution of this paper is a methodology to use a data fusion scheme. The feature extraction was performed based on both colour and morphological information. The strategy was included three steps. In the first step the HSI colour space was used to find the region of interests (ROIs) with red pixels. In the second step, opening and closing operators were used for building morphological profiles. Then, from morphological profile containing original colour image, a statistical feature vector was extracted. Finally, the feature vector was classified by support vector machines based on one-vs.-rest method.

Experimental results show that the proposed method despite considerably reducing in processing time, has given acceptable performance.

The result of this method is dependent to features that are extracted from each image of morphological profile. So, by selecting proper features, someone can achieve much better results.

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