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Traffic Sign Detection and Recognition for Intelligent Vehicle

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***Abstract*—In this paper, we propose a computer vision based system for real-time robust traffic sign detection and recognition, especially developed for intelligent vehicle. In detection phase, a color-based segmentation method is used to scan the scene in order to quickly establish regions of interest (ROI). Sign candidates within ROIs are detected by a set of Haar wavelet features obtained from AdaBoost training. Then, the Speeded Up Robust Features (SURF) is applied for the sign recognition. SURF finds local invariant features in a candidate sign and matches these features to the features of template images that exist in data set. The recognition is performed by finding out the template image that gives the maximum number of matches. We have evaluated the proposed system on our intelligent vehicle SmartVII. A recognition accuracy of over 90% in real-time has been achieved.**

I. Introduction

Traffic sign detection and recognition in real-time is a vital issue in Intelligent Vehicle System and Driver Assistance System (DAS). Although the work in this area can be traced back to the late 1960's, but it has not been until 2000's that real-time performing systems have been successfully achieved [1]-[3]. The traffic sign detection is carried out under the unpredictable complex scene, so there are many difficulties inevitably (Fig.1). (a) Illumination changes, lighting is different according to the time of the day and weather conditions. (b) Scene complexity, many other objects occur in the scene even with some logos and text which are very similar to the traffic signs, sometime the sign may be sheltered. (c) Similarity, some signs are very similar with each other, it makes the recognition a tough challenge. (d) Real-timing, systems require high accuracy and real-time but vast quantities of data processing is a time-consuming task. Our paper tries to deal with (b) and (c) problems. Traffic sign recognition usually consists of two components: detection and classification. First, the location of the traffic signs are found and the target rectangles are extracted in the detection stage. To which category does the candidate sign belong is the main issue needing to be addressed in the classification phase.

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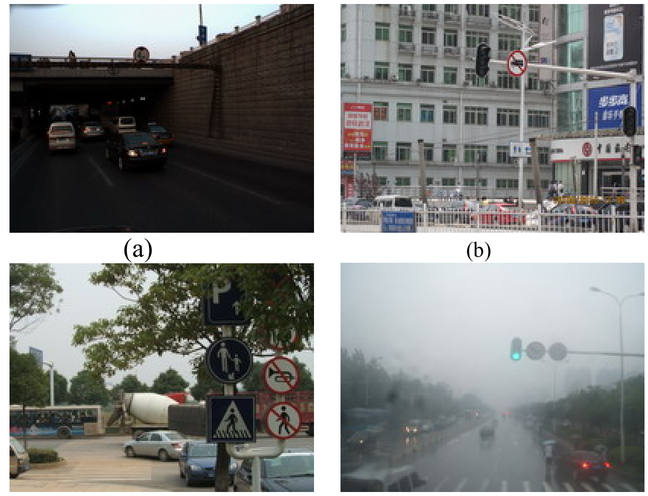

Fig. 1. Examples for difficulties of traffic signs recognition. (a) Illumination deficiency, (b) scene complexity, (c)signs are sheltered, (d) rain day.

A. *Traffic signs detection*

Color segmentation is the most common method. RGB color model is widely used[4]. RGB color space has a higher sensitivity to light intensity. Therefore, HIS and HSV which are not affected by the lighting changes have been used [24][25]. Some other authors also used YIQ [5], YUV, L*a*b [23] and CIE color spaces for the detection. Some authors developed databases of color pixels, look-up tables and hieratical region growing techniques [6]-[8]. Shape-based method is usually used for a final detection after the color segmentation. Many circle, ellipse and triangle detection methods have been used. Hough transform is widely used [9]. [10] discussed ellipse detection in complex scene with neighborhood characteristics and symmetric features of the simple coding. [11] analyzed the color information and geometrical characteristic of the edges to extract possible triangular or circular signs.

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B. *Traffic signs classification*

Many methods have been employed for traffic signs classification such as template matching, LDA, SVM, ANN and other machine learning methods. OCR systems are applied in [12]-[15] used the pictogram-based classification by template matching and cross-correlation. In [16,17], the authors make use of the LDA to distinguish between the road signs. The Multi-Layer Perceptron [18] is widely used in the current approaches. Neural networks are also largely adopted [20][21]. Support vector machines (SVM) are largely adopted to classify the inner part of road signs [19]. Random forests, an ensemble learning technique, are used by [22] to classify signs, and a comparison is made between this technique and SVM and AdaBoost.

In recent years, one of the most accepted and widely used approach in object detection has been proposed by Viola and Jones [22]. Their approach is based on a cascade of detectors, where each detector is an ensemble of boosted classifiers based on the Haar-like features. Inspired by detector presented by [22], we apply this method combined with color segmentation for the traffic sign detection.

The contribution of this paper is that in this paper the traffic signs in china are divided into six classes, for each class, we trained a classifier based on Haar-like features for the detection and the scale invariant feature SURF is used for the sign classification. The detection rate and recognition accuracy has improved slightly. This is a real-time system developed for Intelligent Vehicle specially.

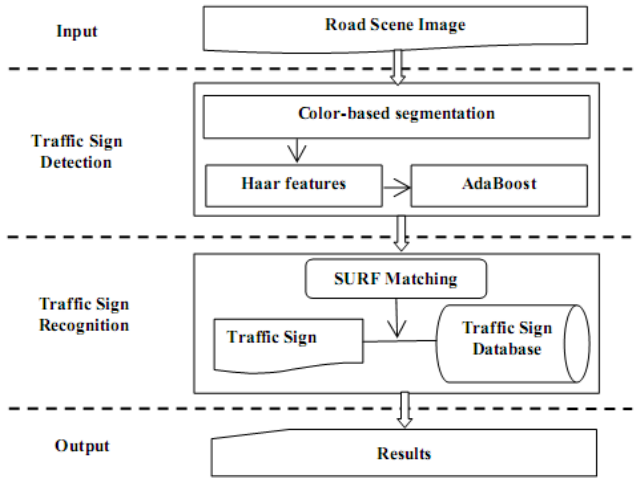


Fig.2. flow chart of traffic signs recognition system

Table 1 Traffic Signs Classes

Type	Shape	Colors	Examples
1	Circle	Red, Blue, White, Black	
2	Upper Triangle	Blue, Yellow, White, Black	
3	Lower Triangle	Red, White, Black	
4	Octagon	Red, White	
5	Square	Blue, White	
6	Rectangle	Yellow, Black	

II. Traffic Sign Recognition System

The proposed sign recognition system is founded on a combination of two components. This includes a detection framework, based on color segmentation, Haar-like wavelet features and AdaBoost, then feature matching method for classification based on the Speeded Up Robust Features (SURF). Fig.2 is the flow of the system. Haar-like features are features of gray images, so the detection method we proposed is mainly based on the gray information, the shape information can mainly affect the haar-like features. So the main traffic signs with which are coped in this paper can be divided into six classes based on shape as show in Table 1. Some other signs such as assist and information signs are not included.

A. *Color-based segmentation*

Color-based segmentation includes two steps: color quantization, ROI locking. In first step, we extract the target color pixels. In the last step, we get the ROI from the pixels based on constraints on bounding box of the connected-components of the pixels. The main color of them include: red, blue, yellow, white and black. Among them white and black always appear with other black. Among them white and black always appear with other three colors. So in our detection method, we focus on the three colors: red, blue and yellow. The RGB color model is highly related to the light intensity. HSV color model is applied in this paper. The Red, Green and Blue values of each pixel are transformed into HSV color values by Eq.1

$$V = \max(R, G, B)$$

$$S = \begin{cases} [V - \min(R,G,B)] * 255 / V, & if \quad V \neq 0 \\ 0, & else \end{cases}$$

$$H = \begin{cases} (G - B) * 60 / S, & if \quad V = R \\ 180 + (B - R) * 60 / S, if & V = G \\ 240 + (R - G) * 60 / S, if & V = B \end{cases} \tag{1}$$

$$H = H + 360, if \quad H < 0$$

Where R, G, B are the RGB color values of a pixel, V is the maximum of R, G, B and H, S, V indicates the hue, saturation and value if the pixel respectively. According to Table

Table 2 Color quantization

	Red	Blue	Yellow
Saturation	S>0.2	S>0.2	S>0.2
Hue	0<H<10 320<H<360	200<H<270	20<H<100

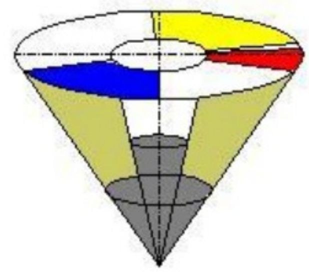
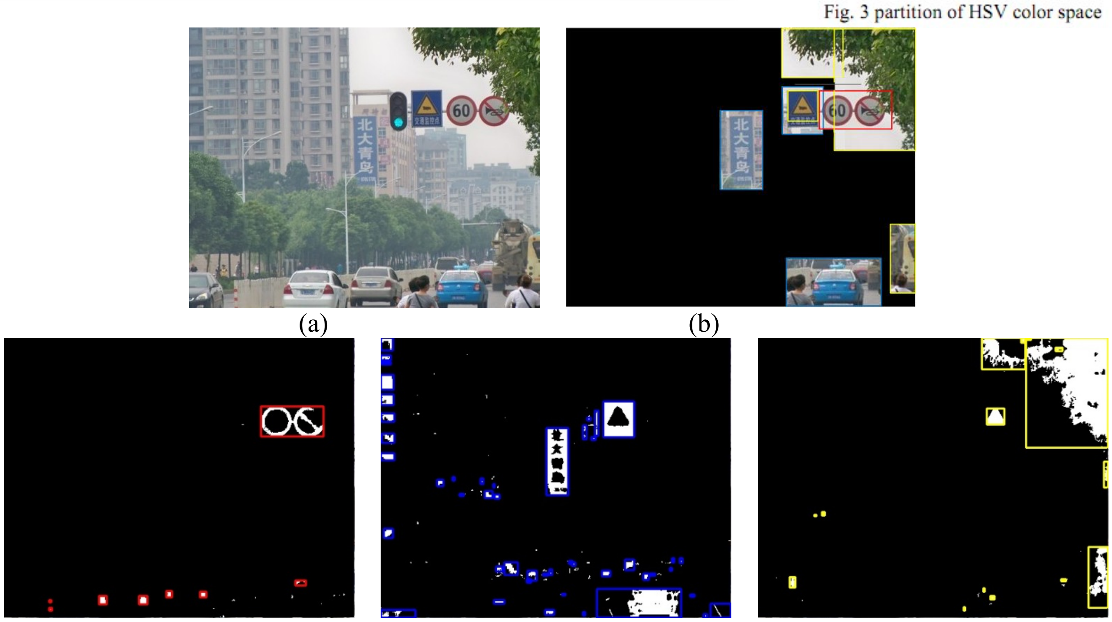


Fig. 3 partition of HSV color space



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

Fig.3 color quantization and ROI locking. (a) original image, (b) ROI locking, (c) red segmentation, (d) blue segmentation, (e) yellow segmentation.

2, we can get the red, blue and yellow pixels from the origin image. Fig.3 is partition of the HSV color space. After the color segmentation, the detected pixels can form some connected regions, then we can get the enclosing rectangles (ER) of them. Based on some constraints on ER, we can wipe off many noise regions. First, the ER smaller than 20×20 pixels are considered as noise and not processed further. Second, the aspect ratio of ER is limited to 2. Third, the saturation of ER is no less than 0.5. The rest of ERs will be considered as the ROIs of the traffic signs.

B. AdaBoost for traffic sign detection

The AdaBoost algorithm is a classifier learning method which combines a set of weak classifiers to construct a strong classifier, then some strong classifiers will be assembled to a cascade classifier. Feature Selection is crucial for classifier. Motivated by the work of Tieu and Viola [22], we use extended Haar-like features to train AdaBoost classifier for traffic signs detection.

$$feature_i = \sum_{i \in (1,n)} w_i \times \mathrm{Re}\,ctSum(r_i) \tag{2}$$

Where w_i denotes the weights of rectangle; RectSum (r_i) is the integral of image by surrounded by rectangle r_i; $feature_j$ is the j_{th} feature; n are arbitrarily chosen, representing the number of rectangles consists of $feature_j$.

C. SURF matching for classification

The proposed recognition method includes three steps: image scaling, SURF features extraction, features matching.

1)Image Normalized

The detected targets found in detection stage will be normalized to be of the same size 100×100 the same as the template which will be matched. Though SURF is a scale invariant feature, in this step we will make sure that the true sign contains enough features can be matched with the template sign. If the number of matched points is lower than a certain value, the candidate will

be discarded as a noise. In order to make sure the certain value is adequate for all candidates, the image scaling is necessary. In this paper, we use bilinear interpolation for image scaling. Once the image normalized, the SURF descriptor can be used for exacting the scale and rotation invariant features.
In our experiments, we trained six classifiers corresponding to the six class signs list in table I. After the detection by the classifiers, the target squares which are exacted from the ROIs will be regarded as the candidates of traffic signs.

2)SURF descriptor

SURF[26][27] detector is chose instead of the often used SIFT detector. SURF is developed to be substantially faster, but at least as performant as SIFT.

In a first step, SURF constructs a circular region around the detected interest points in order to assign a unique orientation to the former and thus gain invariance to image rotations. The orientation is computed using Haar wavelet responses as shown in Fig.4. The Haar wavelets can be easily computed via integral images, similar to the Gaussian second order approximated box filters. Once the Haar wavelet responses are computed, they are weighted with a Gaussian centred at the interest points. In a next step the dominant orientation is estimated by summing the horizontal and vertical wavelet responses within a rotating wedge, covering an angle of $3/\pi$ in the wavelet response space. The resulting maximum is then chosen to describe the orientation of the interest point descriptor. In a second step, the SURF descriptors are constructed by extracting square regions around the interest points. These are oriented in the directions assigned in the previous step. In order to increase robustness to geometric deformations and localization errors, the responses of the Haar wavelets are weighted with a Gaussian, centered at the interest point. Finally, the wavelet responses in horizontal d_x and vertical directions d_y are summed up over each sub-region. Furthermore, the absolute values $|d_x|$ and $|d_y|$ are summed in order to obtain information about the polarity of the image intensity changes. The resulting descriptor vector for all 4×4 sub-regions is of length 64. See Fig.4 for an illustration of the SURF descriptor for three different image intensity patterns. More details about SURF can be found in [26] and [27]. Fig.5 list some SURF features in the traffic signs.

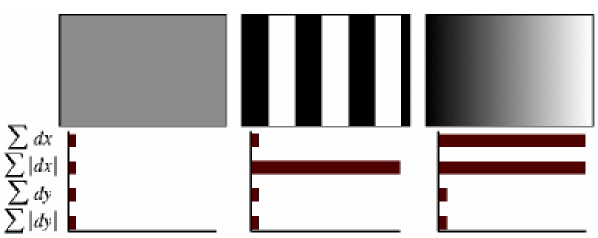


Fig. 4. Illustrating the SURF descriptor

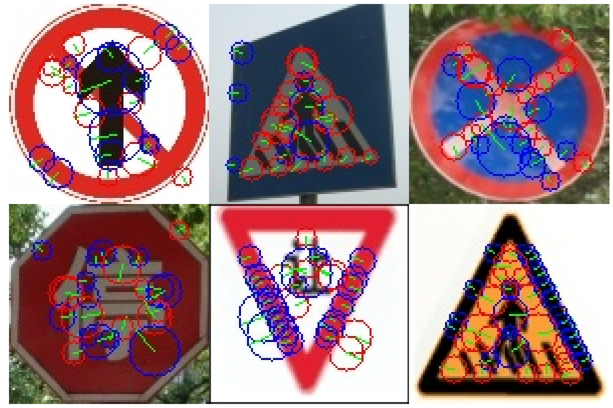


Fig. 5 SURF features in traffic signs. The number of the SURF features is 22, 24, 27, 24, 31 ,40 according to priority.

3)Feature Matching

This process is time-critical. Because we have many template signs should be matched. In order to reduce the match time, All the template signs are divided into eight groups based on the color and the trained adaboost classifiers. We used Approximate Nearest Neighor(ANN)[28] algorithm for matching. SURF features are first extracted from all the template signs which will be divided into eight groups and stored in a database. Then a candidate image is matched by individually comparing each feature from the candidate from the special database selected based the classifier used and color information, then finding matched features based on ANN. The image in template database which gives the maximum number of matches with candidate image is the target class. Fig. 6 shows some match results between the candidate signs and template signs.

Fig.7 SURF feature matching. The number of match points is 16, 11, 24, 7, 12,7 according to priority.

III. Experimental results

The algorithm takes the mobile laboratory SmartV of Wuhan University as the platform. The test image data is acquired by the CCD Video Camera which is mounted on the top of the Chery SUV with a fixed strut. The size of the recorded images is of 640*480. We tested the system under a variety of different conditions. To evaluate the performance of the proposed method, 200 images were taken as test images, in which there are 281 traffic signs.

A. Results of traffic Signs Detection

In this paper, six classifiers were trained for the six classes signs listed in figure 1. For all the classifiers, the number of position samples (PS) and negative samples (NS) is listed in Table 3. Our method can detect road signs in 50 ms. In the 281 signs, there are 265 signs being correctly detected, 14 signs being missing, and 2 signs being false alarm. Thus the detection rates are 94.3%. Thus, the proposed detection method is effective and efficient. Some detection results are shown in Fig.8 to demonstrate that our method is insensitive to many complex conditions. Some failure cases are also shown in Fig.9.

Fig.8. SmartV, which is an intelligent vehicle developed by Wuhan University. It has CCD cameras, lasers, GPS and IMU, etc. Camera labeled is used to acquire road images.

Table 3 the number of PS and NS for the six classifiers trained

	PS	NS
Classifier 1	3125	5200
Classifier 2	1276	2300
Classifier 3	794	1600
Classifier 4	648	1600
Classifier 5	963	1600
Classifier 6	346	1000

B. Results of traffic Signs Recognition

The 265 detected traffic signs are used to evaluate the performance the proposed method. The model database used is shown in table 5. In the 265 signs, there are 244 signs being correctly classified, 14 signs being falsely classified. Thus the recognition accuracy is 92.7%.

Fig.8. Traffic signs detection in the variations of condition.

Fig.9 Failture cases of Traffic sign detection. Detected and missing traffic signs are marked by yellow bounding box and red bounding box.

IV. Conclusions

In this paper, we propose an effective and efficient method for traffic sign detection and recognition in complicated scene. Color quantization is first employed to quickly establish regions of interest (ROI). Sign candidates within ROIs are detected by a set of Haar wavelet features obtained from AdaBoost training. Then, the Speeded Up Robust Features is applied for the sign classification. SURF finds local invariant features in a candidate sign and matches these features to the features of template images that exist in the training set. The recognition is performed by finding out the training image that gives the maximum number of matches. From the experimental results, we can find that the proposed method has high accuracy and fast execution rate. For complicated scene, the detection rate and recognition accuracy are 94.3% and 92.7%, respectively. Moreover, on the average, it takes 170ms and 200ms for detection and recognition, respectively.

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