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Real-time Traffic Sign Detection Algorithm Based on Dynamic Threshold Segmentation and SVM

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Abstract. Detection and recognition of road traffic signs establish a crucial element in Advanced Driver Assistance Systems (ADAS), which can provide real-time road sign information to vehicles. The purpose of conducting research on this topic is introduced to a less complex algorithm that works for traffic signs detection in complicated environment, accurately and rapidly. Initially, according to the color features of traffic signs, a color enhancement algorithm based on linear contrast stretching is used to enhance RGB images, and the color enhanced gray images of each channel are obtained. And then the dynamic thresholds are set according to pixel values of the obtained color enhancement gray maps to segment the images to obtain traffic sign candidate regions. Moreover, quite a few background interference is removed by morphological operation. Furthermore, the histogram of oriented gradient (HOG) features of candidate regions are extracted and SVM classifier is trained to accurately locate the candidate regions to further improve the detection accuracy. We performed some comprehensive experiments on the German Traffic Sign Detection Benchmark (GTSDB) dataset. The accuracy of traffic sign detection exceeded 97.41%. The proposed method has higher detection accuracy and time efficiency than other methods and better robustness under complex traffic environment.

Keywords: dynamic threshold segmentation (DTS), location detection (LD), region of interest (ROI) extraction, support vector machine (SVM), Traffic sign detection (TSD)

1 Introduction

Detection and recognition of road traffic sign establish a crucial technological element in Advanced Driver Assistance Systems (ADAS) [1], which can provide real-time road sign information to drivers and elevate driving safety [2-3].Traffic signs are normally composed of particular colors (red, yellow, and blue) and shapes (round, square, and triangular), which have impressive visual effect in the road environment. Therefore, traffic sign detection (TSD) usually can be classified into color-based, shape-based and color-shape-based methods. Moreover, with the advance of computer performance, there are TSD methods based on machine learning and convolution neural network (CNN) in recent years [4-5].

In color-based TSD, the RGB images are usually transformed into other color space such as HSI [6], HSV [1, 7, 33], Ycbcr [8]. Then the traffic signs are extracted by color thresholding segmentation based on smart data processing. Color-based TSD techniques are easily affected by complex illumination conditions of traffic scenes. In shape-based TSD, geometric contour shapes of traffic signs are detected by means of template matching [9], geometric invariant moment [10], and geometric symmetry [11]. Compared with template matching and geometric invariant moment in a complex illumination environment, symmetry detection has better adaptability, while it requires higher computational complexity. Therefore, the existing color and shape based TSD methods have weaker adaptability under complex brightness conditions. As for CNN based methods, although many state-of-the-art methods have been presented by researches [3], the computational complexity are much higher than the methods

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mentioned above, besides, it requires even higher hardware resources.

In this paper, a two-stage real-time TSD approach based on dynamic threshold segmentation (DTS) and support vector machine (SVM) is proposed. The religion of interest (ROI) extraction and precise location detection (LD) are the main components for our TSD framework. (1) In the ROI extraction stage, the ROI of traffic signs is extracted by using our color-enhanced DTS method, and quite a number of background interference is removed by introducing morphological operations. With this method, the irrelevant foreground objects and background is suppressed, which effectively achieved rapid traffic sign segment effect in complex lighting environments. Therein, we employee the traffic sign preprocessing approach of our previous work [12] to enhance the traffic sign image under extremely abnormal illumination scenes, by the means, the robustness of the traffic sign segmentation algorithm to illumination changes is further enhanced. (2) In the precise location detection stage, histogram of oriented gradient (HOG) features of ROI are extracted and SVM classifier is trained to verify whether the ROI is a target sign. With this method, our method is capable to further accurately locate traffic signs in natural scenes. The sample data of our TSD process are all from the German Traffic Sign Detection Benchmark (GTSDB).

The rest of this paper is arranged as follows. Related works about TSD are described in Section 2. In Section 3, we details the main contributions of this paper, Section 4 shows some experimental results of our method, and Section 5 presents the conclusions and future directions.

2 Related Work

As mentioned in section 1, TSD methods are principally classified into: color information based, shape information based, fusion of color and shape information based, and machine leaning based detection techniques. It is demonstrated in Fig. 1.

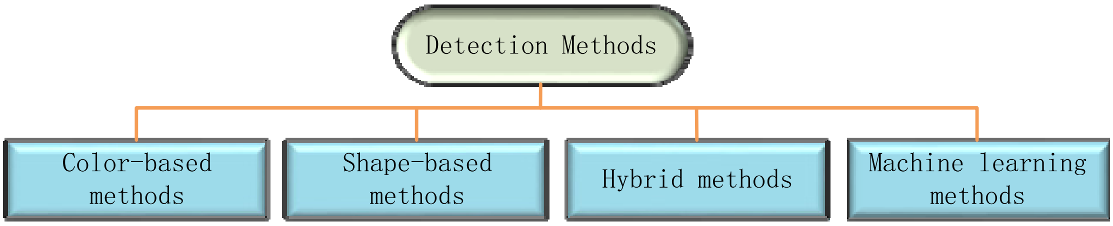


Fig. 1. TSD algorithm classification

Color information based TSD methods typically require the selection of an appropriate color model, and then use color threshold processing or color enhancement processing to extract the ROI in the selected color model. The commonly employed color segmentation technique is the threshold segmentation method based on the RGB color model [13-14]. For example, Escalera et al. [13] sets the thresholds of RGB color channels to perform segmentation of RGB images. The calculation of those methods is simple and the implementation is effortless. However, the RGB color space is sensitive to image brightness, the segmentation effect is easily affected by brightness conditions of a complex traffic environment. To overcome the adverse effects of illumination changes, Moreno et al. [15] described a RGB normalized color space (RGBN), which introduced only two channels to perform classification. For better performance, RGB space is normally converted to other color spaces that are less affected by illumination during color segmentation [6-8, 16]. Although the conversion of color space could lower the influence of illumination to some degree, the conversion of color space requires nonlinear operation, which seriously affects the real-time performance of the method. Some scholars have also attempted to utilize color enhancement to preprocess traffic sign images. For instance, Ruta et al. [17] proposed a color enhancement algorithm for RGB images, which exploits enhanced color brightness to quickly determine and detect the signs. Zaklouta et al. [18] improved the approach of [17] to further drop the effect of illumination on detection.

Shape information based TSD methods utilize different algorithms to segment and locate according to the specific shape features of the signs. The most common shape-based approach is the Hough transformation (HT). Zaklouta et al. [19] applies Hough transform (HT) to properly determine circular and polygonal signs, thus effectively avoiding the influence of light changes. In [20], HT is introduced to detect straight lines to detect traffic signs, but the approach has high complexity. Another popular shape-based detection method is utilizing the shape symmetry of traffic signs. Gu et al. [21] proposed a radial basis symmetric voting method used the symmetry of traffic signs. Zhang et al. [22] proposed an improved fast radial symmetry transformation algorithm for TSD. Shape information based traffic sign detection is more adaptable to complex brightness conditions, while it requires higher computing complexity and the performance is influenced greatly by deformation, rotation, and partial occlusion of traffic signs.

Color and shape information based TSD methods combine color and shape features to enhance detection performance. In [23], color and shape features of traffic signs are integrated into an energy expression form to detect traffic signs. The detection method proposed in [19, 24-26] had better robustness in a complex road environment. However, most of the existing methods are only limited to specific types of traffic signs.

Machine learning based TSD methods have been widely applied in the field of image recognition in recent years, which have been proved to be a great success. There are two most representative methods, one is based on the combination of HOG features and SVM, the other is based on AdaBoost cascade structure [27-28]. Salti et al. [29] adopted SVM classifier to further verified ROI. Wang et al. [30] proposed a cascade detector called hybrid HOG variant cascade for fast TSD, which greatly enhances the detection efficiency. Based on the powerful classification performance of the SVM classifier, it is introduced to our scheme in the subsequent detection phase to eliminate the false detection area. As an essential branch of machine learning technology, the deep learning-based detection method has further increased the accuracy and detection speed. For example, Shao et al. proposed an improved fast R-CNN TSD algorithm based on the second ROI and the highly probable region proposed network in GTSDB, which have achieved considerable performance [31]. Unfortunately, the deep learning-based detection technique has even higher requirements for running resources and hardware configuration, which brings difficulties to the practical application on the vehicles.

In summary, the existing color and shape based traffic sign detection methods have weaker adaptability under complex brightness conditions while the CNN based methods with high performance requires adequate resources. Therefore, we propose a two-stage real-time TSD approach based on DTS and SVM to enhance TSD performance under complex environments.

3 Proposed Method

Our proposed approach is able to significantly enhance the detection velocity and accuracy at the same time under complicated illumination environments. Fig. 2 is the process of our proposed two-stage TSD method. The detection scheme is primarily composed of ROI extraction and location detection, which realizes the determination of the traffic sign region from coarse to fine.

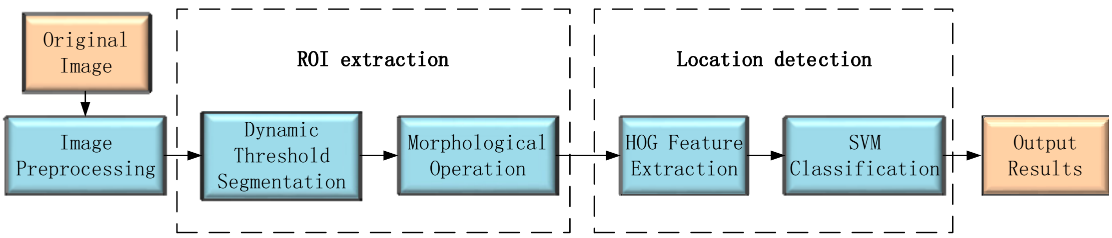


Fig. 2. The framework of the proposed approach

3.1 ROI Extraction

In this part, ROI extraction can be subdivided into two steps: DTS based on RGB color enhancement method and morphological operation.

To enable the method to achieve better real-time performance and adaptable to illumination changes, this paper presents a dynamic segmentation method of color threshold based on RGB method. The color enhancement scheme in [29] is employed to generate color enhanced gray maps of each channel to highlight the three main colors of red, yellow and blue in traffic sign images. Then the dynamic threshold is obtained according to the pixel values of the gray maps for segmentation, thus obtaining multiple traffic sign ROIs.

Specially, for the image $f(x)$, there are three color channels, including red, green and blue. Its red enhanced gray-scale map (represented as $f_R(x)$), blue enhanced gray-scale map (represented as $f_B(x)$) and yellow enhanced gray-scale map (represented as $f_Y(x)$) are given by the following formula respectively.

$$f_R(x) = \max(0, \min(\frac{R-G}{R+G+B}, \frac{R-B}{R+G+B})), \tag{1}$$

$$f_B(x) = \max(0, \min(\frac{B-R}{R+G+B}, \frac{B-G}{R+G+B})), \tag{2}$$

$$f_Y(x) = \max(0, \min(\frac{G-B}{R+G+B}, \frac{R-B}{R+G+B})), \tag{3}$$

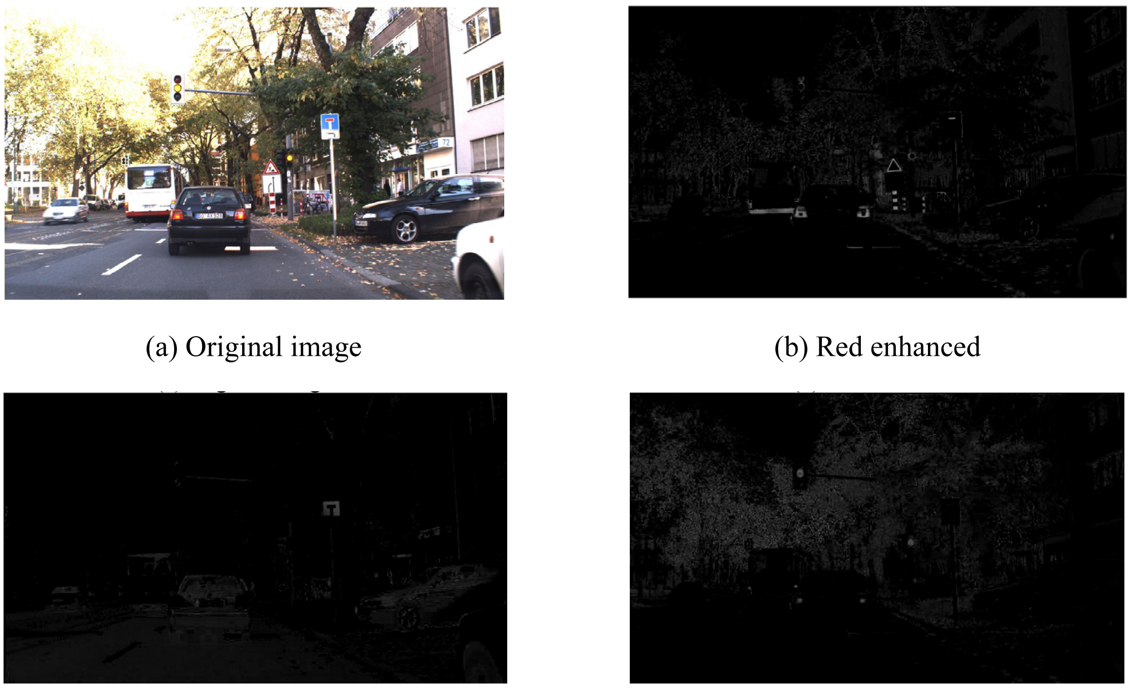
Therein, since the blue component of the blue area in the RGB image is quite close to the value of the green component when the light intensity is lower, the enhancement formula of the blue component are modified to:

$$f_B'(x) = \max(0, \frac{B-R}{R+G+B}), \tag{4}$$

Finally, a color enhanced gray-scale map is obtained:

$$f(x) = \max(f_R(x), f_B'(x), f_Y(x)). \tag{5}$$

The color enhanced gray images of a traffic sign image are shown in Fig. 3. Compared with the irrelevant colors be suppressed, the red, blue and yellow information in the image are more prominent. It proved that the improved method effectively avoids the disadvantage that the classical color threshold segmentation method is sensitive to changes in color and illumination, which is the premise for the threshold segmentation later.



(a) Original image

(b) Red enhanced

(c) Blue enhanced

(d) Yellow enhanced

Fig. 3. Color enhanced gray image

In practical application, the fixed threshold segmentation scheme has some trouble such as sensitivity to illumination changes and difficulty in threshold selection, which makes it difficult to meet the demands of practical application. Since the gray values of the target and the background in the gray image obtained by the above color enhancement algorithm are quite different, we employ statistical methods to set dynamic thresholds in accordance with the pixel gray values of the enhanced image for binary segmentation, and then the ROIs of traffic signs are preliminarily determined. Afterwards, we scan the pixel values of the total image and calculate the mean and variance of the image gray scale. The calculation formula is as follows:

$$\mu = \sum_{i=0}^{m}\sum_{j=0}^{n}\frac{f(i,j)}{mn}, \tag{6}$$

$$\sigma = \sqrt{\sum_{i=0}^{m}\sum_{j=0}^{n}\frac{[f(i,j)-\mu]^2}{mn}}, \tag{7}$$

Where μ and σ represent the mean and variance of all gray values in the enhanced image, respectively. $f(i,j)$ indicates the pixel value of the enhanced gray image at the point of (i,j). m, n are the width and height of the image, separately.

The dynamic threshold could be calculated by equations (6) and (7), as shown in (8):

$$T = \mu + \lambda\sigma. \tag{8}$$

Where λ is the adaptive parameter, it is determined in line with experiments. The range of λ is from 2 to 5. Balancing the effect of bright and dark areas in traffic sign images, we take $\lambda = 3$ as the adaptive parameter. The enhanced image DTS formula for the red, blue, and yellow color channels satisfies:

$$Red(i,j) = \begin{cases} True, & f_R(i,j) \geq T \\ False, & else \end{cases}, \tag{9}$$

$$Blue(i,j) = \begin{cases} True, & f'_B(i,j) \geq T \\ False, & else \end{cases}, \tag{10}$$

$$Yellow(i,j) = \begin{cases} True, & f_Y(i,j) \geq T \\ False, & else \end{cases}. \tag{11}$$

The effect of the proposed DTS method on traffic sign image segmentation is demonstrated in Fig. 4. Our DTS approach could not only well preserve the principal colors of each channel, but also filter out a great deal of background interference, furthermore, it has satisfactory adaptability to color and illumination changes.

(a) Original image (b) Segmented image

Fig. 4. Result of DTS

Unfortunately, for some images, the binary image obtained by the DTS scheme still has several of interference points. Concretely, the captured image may be polluted and obstructed by obstacles, which will result in incomplete segmentation of the sign contour. This not only increases the number of subsequent detection areas, but also brings unnecessary errors to target detection, bringing about false detection. Therefore, binary images are further screened by morphological operation to eliminate some irrelevant interference.

Four arithmetic forms in morphological processing are applied to process the segmented image respectively. The experimental results revealed that when the binary image is processed by open operation, the interference noise and burr phenomena are effectively eliminated, and the edge of the target area is smoother, which has much better performance. Therefore, the open operation is introduced to process the segmented traffic sign images to further eliminate the background interference points.

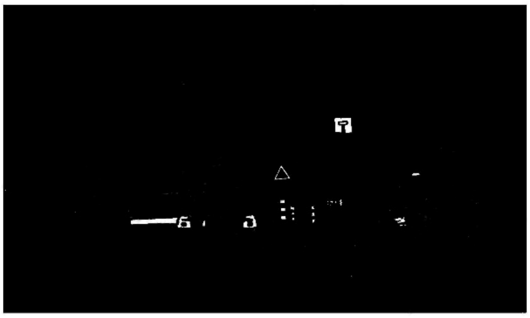


Fig. 5. Result of open operation

3.2 Accurate Detection of Traffic Signs Based on SVM

For traffic sign images, there are candidate regions after DTS and morphological processing. However, for the complexity of the background environment, some interference objects may mistakenly recognized as traffic signs. Besides, there may exist adhesion, fouling and other conditions of traffic signs, which seriously affect the accuracy of detection. To settle the issue, in this part, we take the processing through two measures further, i.e. extracting HOG features of the target region and training SVM classifier to more accurately locate the candidate region, thus filtering out non-traffic sign regions that have been wrongly detected.

Based on the HOG feature extraction method presented by Daal et al. [32], we made some improvements. The specific steps of extracting the HOG feature from the obtained traffic sign ROIs are summarized as follows:

Step 1. The image to be extracted with HOG features is grayed and then normalized to the size of 40×40.

Step 2. The gradient size and direction of each pixel point in the image are calculated.

The normalized image are performed convolution operation by the gradient operator $[-1, 0, 1]$ to obtain gradient components in x direction and y direction respectively, the formula is as follows:

$$G_x(x, y) = n(x+1, y) - n(x-1, y), \tag{12}$$

$$G_y(x, y) = n(x, y+1) - n(x, y-1), \tag{13}$$

Where $n(x, y), G_x(x, y), G_y(x, y)$ represents the pixel value, horizontal gradient and vertical gradient at the pixel point (x, y) respectively. The gradient magnitude and gradient direction of the pixel point are expressed as:

$$G(x, y) = \sqrt{G_x(x, y)^2 + G_y(x, y)^2}, \tag{14}$$

$$\theta(x, y) = \arctan(\frac{G_y(x, y)}{G_x(x, y)}), \tag{15}$$

Step 3. Divide the image into a plurality of cell units with the size of 5×5.

Step 4. Construct gradient direction histograms of cell units.

Firstly, the target image is divided into a plurality of small cell units, each cell contains $n \times n$ pixel points, and then the gradient direction of $0 \sim 180°$ is equally divided into 9 direction intervals with $20°$ as a bin. Finally, the histogram weighted statistics are performed on the gradient directions of all the pixels in the cell in each interval, and take the weighted value as the gradient magnitude of the pixel, so that a 9-dimensional feature matrix is obtained, in which the gradient direction histogram is corresponding to the cell.

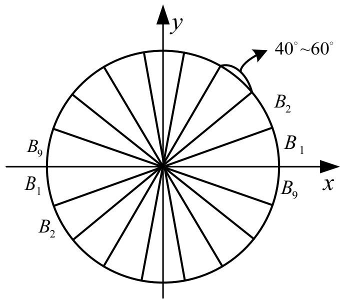


Fig. 6. Schematic diagram of gradient direction mapping

Step 5. Description of region block gradient histogram.

Cells of the same size and adjacent to each other are combined to form a connected region block, and feature vectors of all cells in the block are connected in series to obtain feature description vectors corresponding to the block. In this paper, 2×2 adjacent cells are combined into a block, and the feature vector of each cell is 9 dimensions, so the feature vector corresponding to the block is $2 \times 2 \times 9 = 36$ dimensions.

Step 6. Obtaining image HOG features.

The whole image is scanned along the horizontal and vertical directions by taking a cell size as a step size, and finally the feature vectors of the previously obtained blocks are cascaded, which is the HOG feature of the entire traffic sign image.

For a 40×40 sized traffic sign image, the size of each cell is defined as 5×5, and each block shares 2×2 cells, we can obtain 4×4 blocks. Moreover, each block feature has 36 dimensions, so the final HOG feature dimension of the target image are occupied with $7 \times 7 \times 36 = 1764$ dimensions in total.

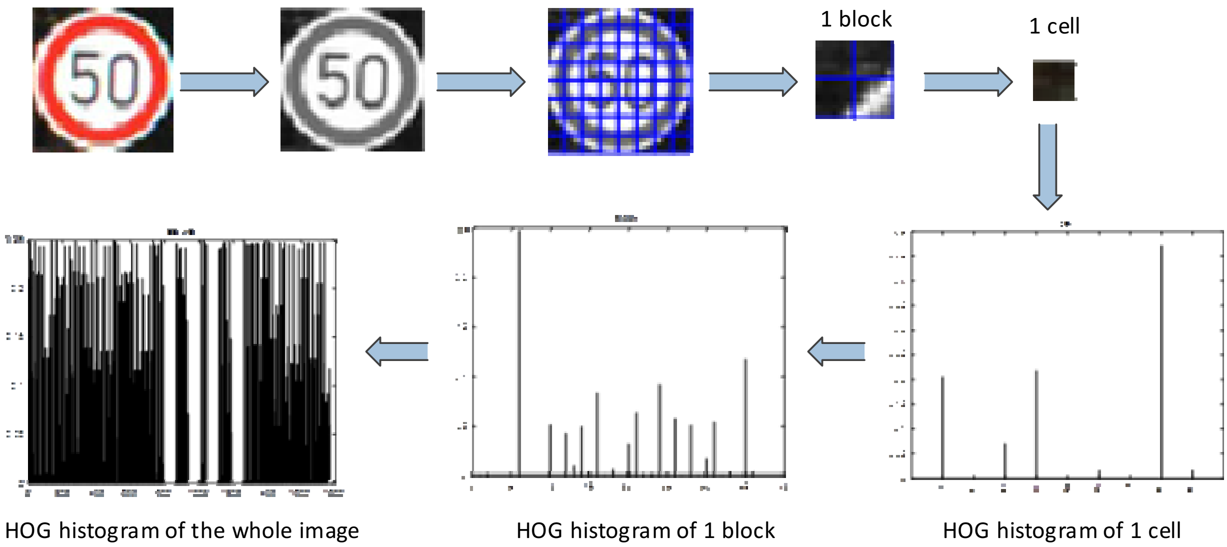


Fig. 7. HOG feature extraction instantiation process

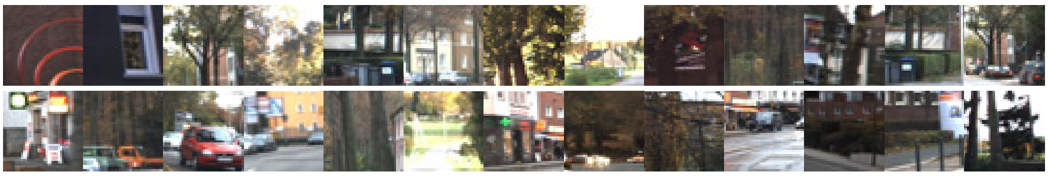
The coarse segmentation result of the DTS algorithm is further refined by training the SVM classifier to eliminate non-sign regions included in the candidate region. The sample data is sorted firstly and the HOG features of all samples are extracted, and then the SVM classifier is trained with the features.

The specific training process is as follows:

Step 1. Training sample data preparation.

The training samples are composed of positive and negative samples. Wherein the positive samples represent the target image to be detected, and the negative samples represent the false target image that is erroneously detected. In this paper, we are required to detect traffic signs in natural scenes, in order to be able to comprehensively reflect the detection performance of the approach, the positive sample set comes from traffic sign pictures in GTSDB, which covers multiple situations in natural road environments such as different illumination, weather, occlusion, defacement and dynamic blur. The negative sample set employs the background picture taken from the GTSDB data set. Some training samples are demonstrated in Fig. 8.

(a) Positive samples



(b) Negative samples

Fig. 8. Partial sample data

Step 2. Sample feature extraction.

Firstly, the positive and negative samples are normalized by bilinear interpolation method, and the uniform size is 40×40. Then HOG features of all sample data are extracted and positive and negative samples are marked separately, therein, positive samples are marked as 1 and negative samples are marked as -1.

Step 3. SVM classifier training.

The HOG features extracted in step2 and their corresponding labels are input into the SVM classifier for training and learning, and the training results are recorded and saved. Since the issue we are required to settle in this paper is an ordinary two-classification problem, linear kernel function is introduced in SVM. According to the color and shape characteristics of traffic signs, the training samples are divided into three major categories, i.e. red circle sign, red triangle sign and blue circle sign. With negative sample, we trained four SVM classifiers in all.

Fig. 9 shows the results of the above morphologically processed images further classified by SVM.

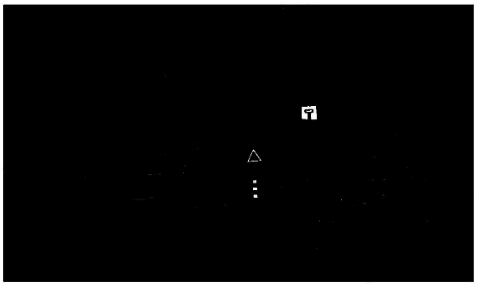


Fig. 9. Result of fine classification by SVM

4 Experiment Results and Analysis

In this segment, a set of experiment is presented to validate the proposed TSD framework. In order to fully verify the effectiveness of the TSD scheme based on DTS and SVM presented in this paper, the detection method is tested experimentally in Intel(R) Core i7, 3.30GHZ, 12GRAM, 64-bit WIN10 operating system, MatlabR2018b employing LIBSVM software package. And the experimental data comes from GTSDB. GTSDB is a public traffic sign dataset, which has 900 images with size of 1360×800 pixels (where 600 images are images for training and others are images for testing). The dataset contains diverse road scenes with apparent changes in brightness and contrast conditions. The sizes of traffic signs' candidate ROIs on the GTSDB range from 16×16 to 128×128. In the experiments, to facilitate statistical evaluation of the method's detection performance, the traffic signs are manually marked on the images.

4.1 Results of ROI Extraction

In order to verify the detection performance of the DTS based method in various environment ranges, a simulation experiment under several conditions is performed. To better demonstrate the performance of our method, comparative experiments is carried out for comparison and analysis in the meanwhile.

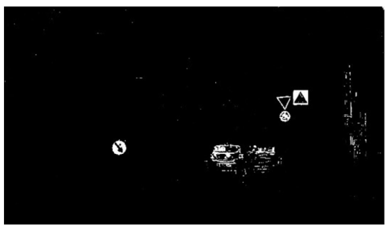
(a) Original image

(b) Re [15]

(c) Re [7]

(d) Re [14]

(e) Re [25]



(f) Proposed

Fig. 10. Results of 5 methods in normal scene


(a) Original image


(b) Re [15]


(c) Re [7]


(d) Re [14]


(e) Re [25]


(f) Proposed

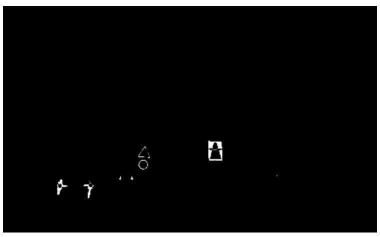
Fig. 11. Result of 5 methods in uneven illumination and complex background scene


(a) Original image


(b) Re [15]


(c) Re [7]


(d) Re [14]


(e) Re [25]

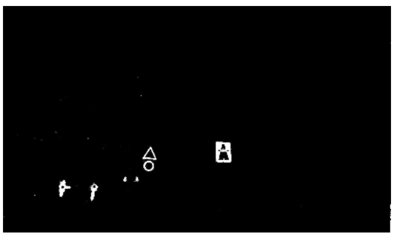

(f) Proposed

Fig. 12. Results of 5 methods in poor illumination scene

Firstly, it’s known that the proposed DTS method can effectively segment the signs in the image, especially the red and blue signs. Besides, it has better performance for removing some background interference information such as vegetation and buildings. Finally, the segmented sign outline is more complete and clear. Table 1 illustrates the time consumption of the five color segmentation methods.

Table 1. Comparison of time consumption of segmentation methods

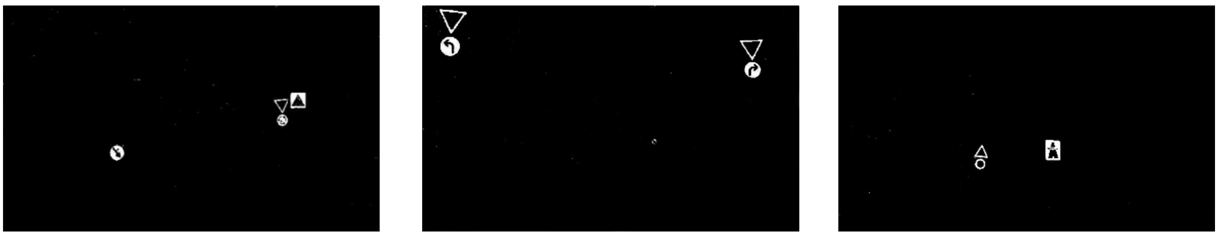
Segmentation Method	Re [15]	Re [7]	Re [14]	Re [25]	Proposed
Time-consuming (ms)	49.2	65.5	57.8	60.1	**58.3**

By comparing the segmentation results and performance of the mentioned approaches, we could draw a conclusion that the DTS method is significantly better than Re [15] and Re [7]. The method in Re [7] exists a nonlinear process in space conversion, which takes some time and declines the real-time performance of the system. Compared with RGBN segmentation in Re [15], the scheme in this paper shares more time, however, the segmented signs are clearer and the background interference is much less, which reduces interference areas for the subsequent fine detection process, thus meeting the real-time requirements of the detection system. What’s more, the time consumption is closed to method in Re [14] and Re [25], fortunately, the consequence of segmentation is sounder than these two methods.

4.2 Results of LD

There may be interference of similar elements in the image after the ROI extraction in the first stage. To settle the issue, further screened through the trained SVM is carried out. The figure below demonstrates the results of the above three conditions after SVM fine classification.

(a) Original image



(b) Results after SVM fine classification

Fig. 13. Results of LD

4.3 Results of TSD in Actual Scenes

In our experiment, 1846 red circle signs, 1910 red triangle signs and 1430 blue circle signs are randomly selected from GTSDB as the trained positive samples. At the same time, 4720 false target images are taken as the trained negative samples. Then 548 traffic sign images in natural scenes are randomly chosen as the test samples, including 789 signs in total, and the detected signs are outlined by green box. Traffic sign images under various weather conditions (such as sunny and rainy days) and different illumination conditions (such as backlight, dark light, etc.) are contained in positive and negative samples. Some experimental results are shown in Fig. 14.

(a) Normal viewing angle, lighting scene

(b) Backlight, small signs scene

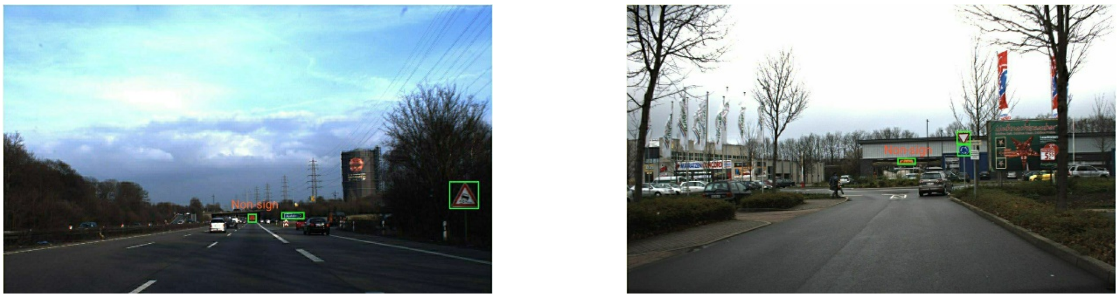
(c) Low illumination, multipe signs scene

Fig. 14. Partial results of detection in actual environment

For severe poor illumination images, we employ our traffic sign image enhancement method in low light environment proposed in [12]. Therefore, the proposed scheme are adaptable to illumination changes in complex environments, which has favorable robustness and real-time performance. However, for traffic signs that account for a small proportion of pixels in the image, or objects that are extremely similar to the target signs, there are missed and false detections. The samples are as displayed in Fig. 15.

The missed detections and false detections are marked in the traffic sign images. The main reason of the missed detections is that traffic signs are positively small in the middle of the image or have serious fading, resulting in incomplete segmentation during color segmentation. The dominating reason of false detections is that there are interfering objects that are quite similar to the color and shape features of traffic signs. Similar to the trained samples, the traffic sign test samples are divided into three categories according to their color and shape characteristics, therein, the total number of signs, positive samples, missed samples and false samples included are counted respectively, and the corresponding detection rate is calculated. The experimental results are demonstrated in Table 2.

(a) Missed detections



(b) False detections

Fig. 15. A small number of missed and false detections

Table 2. Experimental data of TSD in our method

Types of samples	The number of signs	Positive number	Missed number	False number	Accuracy
Red & circle	341	328	6	7	96.78%
Blue & circle	172	164	5	3	97.14%
Red & triangle	291	279	7	5	96.89%

4.4 Performance Comparisons

To verify the performance of the proposed detection approach more intuitively, different methods are introduced to measure on the same data set. The detection method based on the combination of DTS and SVM in this paper is compared with several similar methods, i.e. the color enhancement based segmentation method in Re [17], the classical HOG + SVM based method in Re [29], the HSV segmentation and SVM classification based method in Re [33], the adaptive color threshold segmentation and shape detection based method in Re [14], and the estimated global threshold value with SVM+KNN based method in [25]. The comparisons are carried out in terms of detection recall ratio, precision ratio, accuracy and running time. The evaluation criteria for some indexes are expressed as follows:

$$\text{Recall ratio: } recall = \frac{TP}{TP+FN}, \tag{16}$$

$$\text{Precision ratio: } precision = \frac{TP}{TP+FP}, \tag{17}$$

$$\text{Accuracy: } accuracy = \frac{TP+TN}{TP+TN+FP+FN}. \tag{18}$$

Where TP is the number of traffic signs that are correctly detected and FP is the number of traffic signs that are falsely detected, FN represents the number of missed detections, and TN indicates the number of non-target candidate areas that are eliminated. Table 3 illustrates the performance indicators of detection schemes mentioned above.

Table 3. Performance comparisons

Method	Missed number	False number	Accuracy	Recall ratio	Precision ratio	Running time (s)
Re [17]	64	56	86.22%	91.84%	92.78%	0.064
Re [29]	33	29	90.16%	92.45%	93.30%	0.174
Re [33]	26	23	94.03%	96.51%	96.90%	0.212
Re [14]	23	20	96.72%	97.17%	**97.52%**	0.168
Re [25]	19	22	97.06%	97.04%	96.58%	0.156
Proposed	**14**	**19**	**97.41%**	**97.89%**	97.15%	**0.127**

It could be concluded from Table 3 that the color enhancement method of Re [17] has the faster detection speed, whereas there are many missed and false detections. In Re [29], the HOG+SVM method has improved the performance compared with Re [17], but the accuracy is relatively lower. Re [33] takes the longest running time for detection, since the conversion from RGB to HSV took a certain amount of time. The performance of Re [14] and Re [25] are similar to the proposed method, in Re [14], the precision is even higher. However, the accuracy is lower than ours and their running time is longer. From the comparisons, we know that our method is capable to quickly and accurately detect the traffic signs in complex environments, which has competitive performance.

5 Conclusion

This paper studied the real-time TSD method based on the two-stage fusion strategy of the actual and complex road environment. The approach is divided into two stages: coarse extraction of ROI and accurate positioning by SVM. In the coarse extraction stage, on the basic of the significant color features of traffic signs, the DTS algorithm is designed to segment the image to obtain traffic sign candidate regions, and a large amount of interference is removed through morphological processing. In the fine positioning stage, SVM classifier based on HOG features is employed to accurately detect candidate regions, eliminating a great many of false detection signs and further improving the accuracy. In the experiment, GTSDB are selected as our data set. Moreover, the proposed scheme and similar methods are respectively adopted for comparative experiments, which prove the effectiveness and real-time performance of the described detection approach. For the issue of false detection due to the existence of similar objects and the matter of missed detection caused by the small proportion of pixels occupied by traffic signs in the entire image, which is the focus of our next work.

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