An Improved Traffic Signs Recognition and Tracking Method for Driver Assistance System

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***Abstract*—We introduce a new computer vision based system for robust traffic sign recognition and tracking. Such a system presents a vital support for driver assistance in an intelligent automotive. Firstly, a color based segmentation method is applied to generate traffic sign candidate regions. Secondly, the HoG features are extracted to encode the detected traffic signs and then generating the feature vector. This vector is used as an input to an SVM classifier to identify the traffic sign class. Finally, a tracking method based on optical flow is performed to ensure a continuous capture of the recognized traffic sign while accelerating the execution time. Our method affords high precision rates under different challenging conditions.**

Keywords—traffic signs detection; traffic signs classification; traffic signs recognition; traffic signs tracking; SVM; HOG

I. Introduction

Traffic signs (TSs) recognition is a main issue for a driver assistance system as it has a dual role to control the road traffic as well as warning and guiding the driver. Serious accidents happen when drivers miss signs due to distractions or psychological state of drivers [1,2]. Therefore, automated recognition of traffic signs is an important topic for autonomous navigation systems. Such system has to be fast and efficient to detect traffic signs in real-time context and identify them precisely. Moreover, they have to handle complex problems which can hinder detection and recognition effectiveness. These problems include variations in illumination (light levels, twilight, fog, rain, and shadow), motion blur and signs occlusion. Effectiveness is a key thought, as one misclassified or undetected sign could affect the navigation system.

Actually, the existing systems do not provide a guarantee 100% of accuracy. This has motivates many researchers to improve the performance of traffic signs detection, tracking and recognition in complex conditions and so is the objective of our herein presented method. Hence, we introduced a new method for fast detection, tracking and classification of traffic signs from a moving vehicle in complex conditions. In the detection step, we apply a color based segmentation method to extract the candidate regions of traffic signs. For the classification step, HoG features are applied to encode the detected traffic signs and compute the feature vector. This vector is used as an input to a SVM classifier to identify the traffic sign class. Finally, we track the recognized traffic signs using an optical flow-based method to keep a constant capture of the identified traffic sign.

The following section is dedicated to a brief study of traffic sign recognition and tracking process and overviews the existing methods. The outlines of our proposed approach are presented in details in section 3. The experimental findings and results will be detailed in section 4. The last section will wrap up the discussion by providing a conclusion and some reflections on our future research studies.

II. Related Works

The recognition of TSs is mainly performed using three steps: detection, classification and tracking. The detection step seeks to reduce the search space and indicate only potential regions which could be recognized as possible TSs. In the classification step, each of the already detected candidates regions is filtered to decide whether it is a traffic sign or not. As for tracking step, it helps to reduce the time processing of traffic sign while keeping a continuous focus on the classified traffic sign.

In this section, we detail existing methods in the literature for TS detection, classification and tracking (Table I).

A. Traffic Sign Detection

In the detection step, the image is segmented relying on the visual key of traffic signs features such as color and shape.

In fact, traffic signs colors represent basic information as the TSs contain bright primary colors that contrast strongly with background environments. Therefore, many methods proceed with a segmentation stage within a specific color space. Typically, the output of a mounted camera is an RGB image. Whereas, the RGB color space is not suitable for the detection of signs' colors due to its sensitiveness to the illumination variations. Therefore, some authors [3] used a color ratio between the intensity components of RGB, while others [4] used only one RGB component as a reference to detect the sign colors in the image. To reduce the dependency on illumination variation, the Hue Saturation Intensity (HSI) system [5] and HSV [6] has been frequently used.

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In contrast, there are methods based on the TS shape which totally ignore color information and focus on shape information from gray scale images. For instance, the technique of local radial symmetry was implemented to detect the points of interest in the TS image [7]. This technique is applied on the gradient of a gray scale image and used a center point votes for circular signs and a line votes for regular polygons. Authors in [8] used the Hough transforms techniques to detect the rectangles, triangle and circles shapes of traffic signs.

B. Traffic Sign Classification

Once the candidate traffic sign regions have been detected, a classifying step is performed to make the decision to keep or reject a candidate region of traffic sign.

To ensure a prominent classification, there are training-based methods and model-based methods. The training-based methods rely on a training phase wherein different artificial techniques, such as Neural Network [9, 10] and Support Vector Machine [11], can be applied. They perceive TSs as a global entity whose characteristics and deformations are learned. Indeed, they require some prior knowledge about the TS structure.

The training-based methods using the neural networks with their different topologies have been widely exploited. In fact, some authors used a convolutional neural network [9] while others applied the radial-based neural networks [10]. The SVM classifier has also been widely employed to identify the corresponding TS class [11]. In addition, the Adaboost algorithm has been also used to classify TSs using a set of week classifiers [12].

Another group of works have based their identification process on TSs models. In fact, the TS region is compared to a set of TSs Template exemplars (models) labeled with discrete class in order to find out the most similar TS class. To perform TSs matching, some comparison metrics are used like the normalized correlation between the templates stored in the database and the potential TS regions [13].

C. Traffic Sign Tracking

Different methods were proposed to carry out the tracking step. These methods can be classified into two classes, namely points-based methods [24] [25] and model-based methods [22]. The points-based methods represent the traffic sign in consecutive frames through a point or a set of points. They perform the tracking throw the matching of a set of interest points extracted from the detected traffic sign. They are generally robust to illumination changes and affine transformations. The model-based methods represent the traffic sign appearance by modeling their shape or/and color. The problem is that this shape may not include certain parts of the traffic sign and may include parts of the background. Hence, it highly depends on the traffic signs detection accuracy.

Based on the aforementioned advantages of existing approaches, we have defined the appropriate methods to use in our proposed solution for traffic sign detection, classification and tracking. For the detection step, we opted for a color based methods since it provides a faster focusing on the potential areas of traffic signs. In fact, similar objects to the traffic signs shapes may coexist in the background like windows, mail boxes and cars. Besides, methods based on shapes require robust edge detection algorithm which is not an easy task with a not head-on viewing angle or with low resolution traffic sign capture. For classification step, we used a SVM classifier thanks to its performance in statistical learning theory and robustness already proved in TRS topic [11]. Concerning the tracking step, we performed with a points-based method thanks to its invariance to illumination changes and affine transformations.

III. OUR PROPOSED TRAFFIC SIGN RECOGNITION AND TRACKING METHOD

In our context of study, we are interested to recognize and track danger and prohibitory traffic signs since they constitute the important cause of accident-prone situations [28]. As Shown in Fig.1, our proposed method is composed of two steps : Traffic signs recognition and tracking.

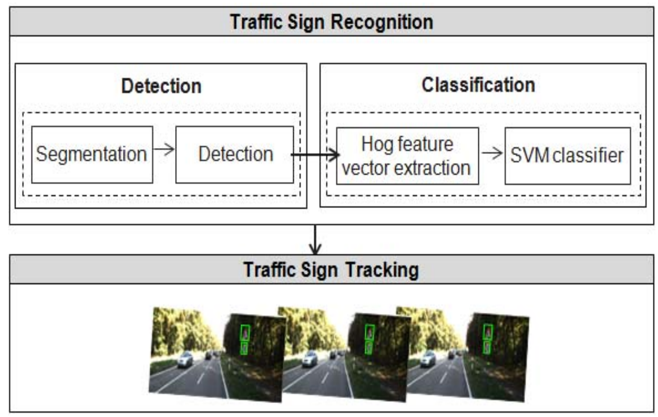


Fig. 1. The proposed traffic sign recognition and tracking process

Relying on our previous introduced lane detection method [14], we detect the lane limits in the closest regions of the images. Next, these lane limits are used to delimit the region of interest where potential TS may exist.

A. Traffic Sign Recognition

The traffic sign recognition performs on two steps: detection and classification.

1) Traffic Sign Detection

The traffic signs detection aims to find out the potential road signs regions.

a) Delimitation of ROI_{TS}

Through simple image processing techniques, we create a reduced search mask to perform the detection step and reduce the search effort for these signs. Therefore, we apply a discarding process to reject TSs that belong to other roads. Hence, we applied our proposed algorithm for lane limit detection proposed in [14]. Relying on the detected lane limits in the near region (ROI_r and ROI_l) (Fig.2 (a)), we used the right lane limit and the Horizon line (Hz) to draw a quadrilateral on the right side of the image (Fig.2 (b)). This quadrilateral is considered as our new Region Of Interest (ROI_{TS}).

TABLE I. TRAFFIC SIGNS DETECTION, CLASSIFICATION AND TRACKING METHODS

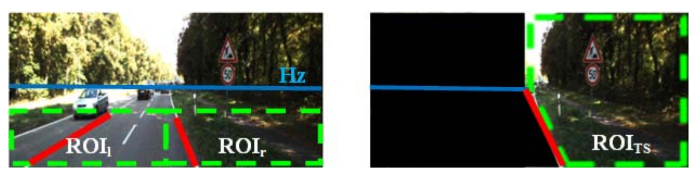
Method		***Description***	***Technique***	***Reference***
Traffic sign detection methods	Color-based methods	These methods are based on the traffic signs colors which are highly visible contrasting colors and thus easily to discriminate from the background. Many space colors have been used to extract the traffic signs colors from the input image.	Thresholding space color	[3]
	Shape-based methods	These methods are based on the traffic signs shapes which have well-defined measures and forms. They require some previous knowledge about shape recognition methods.	Radial symmetry	[7]
			Hough Transform	[8]
Traffic signs classification Methods	Training-based methods	These methods perceive the traffic signs classification issue as a multi-class classification problem. These methods aim to build a traffic sign model from a set of labeled training data.	Neural Network	[10]
			SVM	[11]
			Adaboost	[12]
	Model-based methods	These methods perform traffic signs matching using some comparison metrics between the traffic signs templates stored in the database and the potential traffic sign regions.	Template matching	[13]
Traffic signs tracking Methods	Points-based Methods	These methods represent the detected traffic sign as a set of relevant points. The association of the points is based on the previous traffic sign state which includes the sign position and the vehicle motion parameters.	Kalman Filter	[24]
			Particle Filter	[25]
	Model-based Methods	These methods are based on traffic signs appearance representation, by modeling their shape and/or color.	Camshift	[26]

b) Segmentation

In this step, we proceeded with color segmentation within this ROITS. In fact, the measured color of a TS is often a mixture of the TS original color and the added outdoor lighting. Therefore, the color model for TS segmentation should be seemly selected. As it is commonly known, the color used in TSs seeks to capture the human attention. Therefore, we selected the HSV color space as it is based on human color perception [15]. Indeed, the hue value is invariant to light and shadows variation in daylight [15]. Applying a thresholding on each of HSV component, we segmented the TSs appearing on the ROITS (Fig.3 (a)). Then we apply a closed morphology operation to have more compact areas of interests and eliminate interruptions (Fig.3 (b)).

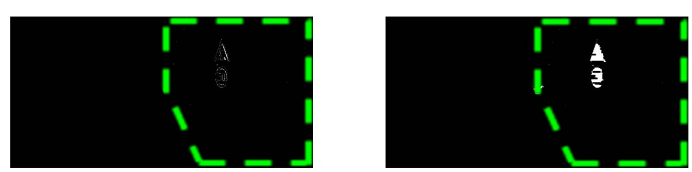
c) Detection

This step aims to detect the precise location of the TSs. In order to achieve this goal, an analysis of the segmented regions is carried out. Therefore, we labeled the connected regions so that all the connected candidate pixels are grouping as one potential region (using 8-neighbors). Next, a bounding box characteristic (height, width, area) is calculated for all potential regions.



(a) Lane limit detection (b) Delimitation of ROI_{TS}

Fig. 2. Delimitation of the region of interest (ROI_{TS})



(a) HSV thresholding of ROI_{TS} (b) ROI_{TS} after closed transformation

Fig. 3.Traffic sign segmentation

Thus, we define a set of potential regions R = {R1, R2, …, RN} where N is the number of potential TSs regions. A several constraint rules based on shape properties [12, 16] are applied to each potential region in order to eliminate regions that cannot be a TS. Therefore, for every potential region, we checked the following rules:

- The height and the width of every potential TS region should be greater than 14 and lower than 100.
- The area of every potential TS region has to be greater than 30% and less than 80% of the corresponding minimum bounding box area.
- The rate of height and width of a potential TS should be an interval of [0.5, 1.5]

Accordingly, these rules allow reducing the number of potential TS regions which helps accelerating the process and improving the accuracy. These regions are going to be the input of the next classifying step (Fig. 4).

Fig. 4. Potential Traffic sign detection

2) *Traffic sign classification*

The classification of potential traffic sign regions is a key step since it helps to make a decision to keep or reject a potential traffic sign. To ensure a prominent classification, we applied the Histogram of Oriented Gradients (HOG) operator to extract the HOG feature vector. Next, an SVM classifier is applied relying on the already extracted feature vector.

a) Feature vector extraction

The Histograms of Oriented Gradients (HOG) is one of the well-known features for object recognition. The HOG features imitate the visual information processing in the human brain. They are able to deal with local changes of appearance and position [17]. The appearance and shape of local object are often described rather well by the distribution of local gradients intensity or edge detection. Thus, the HOG features are calculated using the orientation histograms of edge intensity in local region. Since that traffic symbols are composed of strong geometric shapes and high-contrast edges that encompass a range of orientations, we find that applying HOG features is suitable in our context of study.

In our proposed method, each potential TS region is normalized to 32×32 pixels. Then, the region is divided into 12×12 non-overlapping local regions. The HOG features are extracted from each one of the local region. Histograms of edge gradients with 9 orientations are calculated from each of 4×4 local cells. These histograms capture local shape properties and are invariant to small deformations. The gradient at each pixel is discretized into one of 9 orientation bins, and each pixel "votes" for the orientation of its gradient. The size of the HOG feature vector (N) is computed using (1) :

$$N = \left(\frac{R_{width}}{M_{width}} - 1\right) \times \left(\frac{R_{Heigth}}{M_{Height}} - 1\right) \times B \times H \tag{1}$$

Where R is the region, M is the cell size, B is the number of cells per block, and H is the number of histograms per cell. The values used were : R = 32×32, M = 4 × 4, B = 3, and H = 9.

b) SVM Classifier

In our study, we are interested to recognize the 25 danger and prohibitory TSs since the reduced concentration on them constitute the major accident-prone situations [19].

To build our TSs recognition system, we have proceeded with SVM classifier thanks to its performance in statistical learning theory. Actually, Support Vector Machine is an efficient technique for classification [18] which carries out an implicit mapping of data into a higher dimensional feature space. Given a training set of labeled examples $A=\{(x_i, y_i), i= 1 \ldots n\}$ where $x_i \in R_n$ and $y_i \in \{1, -1\}$. A new test data x is classified using the decision function f(x) defined by (2):

$$f(x) = \operatorname{sgn}\left(\sum_{i=1} a_i y_i K(x_i, x) + b\right) \tag{2}$$

Where α_i are the Lagrange multipliers of a dual optimization problem, and $K(x_i, x)$ is a kernel function.

Given a nonlinear mapping ϕ that embeds input data into feature space, kernels have the form of (3):

$$K(x_i, x_j) = (\phi(x_i).\phi(x_j)) \tag{3}$$

SVM finds a linear separating hyper plane with the maximal margin to separate the training data in feature space. b is the parameter of the optimal hyper plane.

Since SVM classifier makes binary decisions, multi-class classification here is accomplished by a set of binary classifiers together with a voting scenario. Thereby, we have represented each TS region by an HOG features vector. Then, a SVM classifier is applied to find out the separating plane that has maximum distance to the closest points (support vector) in the training set. Fig.5 shows results of classifying correctly two traffic signs

Fig. 5.Classified traffic signs

B. *Traffic Signs Tracking*

Once a traffic sign is recognized, we perform a monocular tracking step in order to have a continuous capture of the traffic sign while accelerating the execution time. Since we are in a moving camera context, it is more appropriate to use an optical flow -based method. Thus, we apply the Lucas-Kanade tracker [20] as it has a high performance to find the exact match under illumination changes and affine transformation. The bounding box which involves the detected TS includes a set of interest points that we extract using Harris detector. For each interest point, the tracker searches for the matching point in the next frame within a padded region around the TS location in the previous frame.

IV. PERFORMANCE EVALUATION OF OUR PROPOSED METHOD

In order to evaluate the performance of our proposed method, we carried out a series of experiments on the "German Traffic Sign Detection Benchmark (GTSDB)" data set [21] which is composed of 51.839 images assessed in 43 classes. We have selected red-bordered traffic sign images which show deformation due to viewpoint variation, occlusion due to obstacles like trees, building etc., natural degrading and weather conditions.

We evaluate the performance of our method with the most known ones in the literature in order to demonstrate the advantages of our proposed techniques. For this evaluation, we proceeded in two steps by applying a qualitative and a quantitative evaluation.

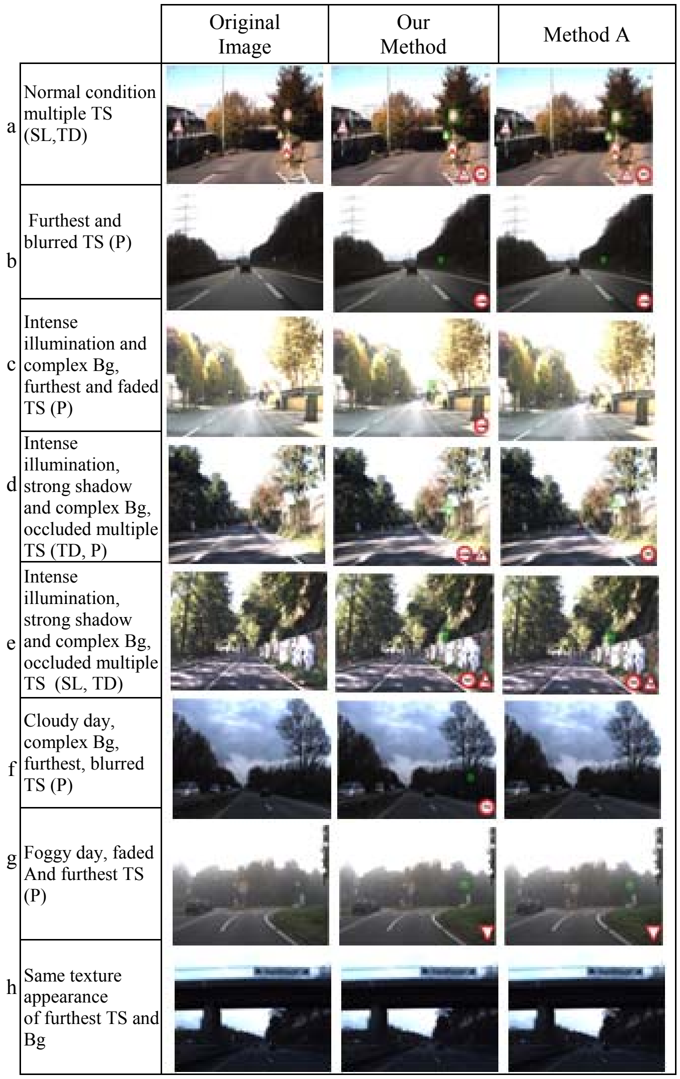
A. *Qualitative Evaluation*

For this evaluation, we compared our solution with the method proposed by Long et al [12] (Method A) which had proved its performance in real time environment condition. We have implemented it according to their corresponding manuscript.

We illustrate in Fig. 6 the recognition results of the two methods on some images illustrating different conditions. The first column describes the different environment conditions; the second column illustrates the original images; and the following columns illustrate successively the TS recognition results obtained by our proposed method and Method A.

The two methods give good detection and classification results in normal conditions where the texture of the TS is clearly discriminated from the texture of the background (Fig. 6 (a and b)). They also give good results in the case of faded and furthest TS during a foggy day (Fig. 6 (g)). The robustness of our method compared to Method A with regard to the considered examples is seen in frames presenting a combination of strong shadow, intense illumination and complex background where the TS are faded and occluded (Fig. 6 (c and f)). These performances are obtained thanks to the efficiency of our Hog feature vector descriptor. As discussed previously, Hog feature are able to deal with local changes of appearance and position of TS [3]. In fact, traffic symbols are composed of strong geometric shapes and high-contrast edges that encompass a range of orientations, thus we find that applying HOG features is suitable to deal with challenging road conditions.

Thus, according to this evaluation, our method overcomes the majority of the road and weather challenges. Nevertheless, the detection and classification fail in some critical situations such as the presence of intense rain and confusion of the TS's texture with the background (Fig. 6 (h)).



* SL: Speed Limit sign, TD: Triangular danger sign, P: Prohibitory sign.

Fig. 6.Qualitative performance evaluation of the two methods.

B. *Quantitative Evaluation*

In order to further evaluate our traffic sign recognition method, we first compared its performance with Method A in terms of Recall, Precision and F-measure [23].

The performance measure of the two methods is given in Figure 7. We note that our method gave an average improvement of 2.53% in the Recall rate, 3.56 % in the Precision rate, and 3.12% in the F-measure rate.

Remember that when a TS is recognized, we perform a tracking step to follow it in the next frames using Lukas-Kanade detector. Fig. 8 illustrates our tracking process. We notice that the Harris features which characterize the detected TS are efficiently matched from one frame to another. Such tracking step helps to reduce the time processing in the following frames.

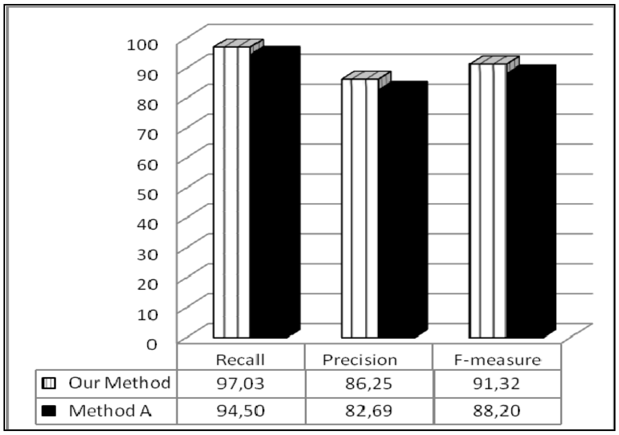


Fig. 7.Comparative performance evaluation of the two methods

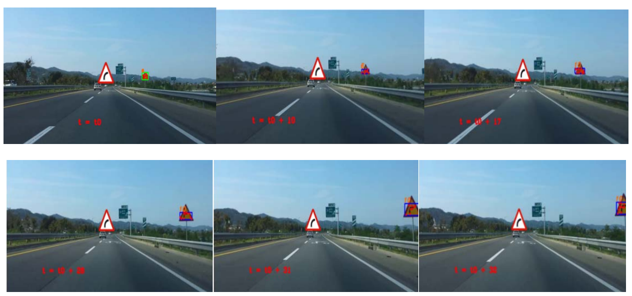


Fig. 8.Traffic sign tracking

V. CONCLUSION

In this paper, we introduced a new method for recognition and tracking of traffic signs dedicated for an automatic traffic assistance system. Potential traffic signs regions are detected, then classified using HOG features and a linear SVM classifier. Afterwards, we keep tracking traffic sign so as to have a continuous capture of the traffic sign while accelerating the execution time. The proposed system shows good recognition rate under complex challenging lighting and weather conditions.

As future work, we aim to experiment other feature descriptors and classifiers as well as comparing the performance of our method with the most recent methods.

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