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North-American Speed Limit Sign Detection and Recognition for Smart Cars

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***Abstract*—Traffic sign detection and recognition system is becoming an essential component of smart cars. Speed-Limit Sign (SLS) is one of the most important traffic signs, since it is used to regulate the speed of vehicles in downtown and highways. The recognition of SLS by drivers is mandatory. In this paper, we investigate SLS detection and recognition system. We focus on North-American speed limit signs, including Canadian and U.S. signs. A modified version of Histogram of Oriented Gradients (HOG) is used to detect and recognize SLS through a set of two-level SVM-based classifiers. Moreover, we build our online database called North-American Speed Limit Signs (NASLS) which includes four SLS categories; white, yellow, black and orange signs. We show through an extensive set of experiments that our system achieves an accuracy of more than 94% of SLS recognition.**

I. Introduction

With the advent of new generation of smart cars, traffic sign detection and recognition system is becoming one of its essential components. Speed-Limit Signs (SLS) category is one of the most important traffics signs, since they are used to regulate the speed of vehicles on traveling areas. The non-respect of maximum speed limit signs by inattentive drivers may lead to fatal traffic accidents. That is, automatic SLS recognition system is needed to recognize signs, and alert drivers.

In general, the *detection* and *recognition* of SLS involves two steps: the *detection* of potential candidates Regions Of Interest (ROI) which possibly contains the signs, and the *recognition* of these ROI to extract the correct type of signs. The detection of SLS is usually performed through color (e.g., red) or shape (circular or rectangular). From the reviewed literature, the detection of rectangular signs is generally performed through shape-based methods, for example [16], which increases the detection rate in harsh condition (e.g., night). While the circular signs are frequently detected through shape and/or color-based methods, for instance (see [17]).

The second step of SLS recognition system, i.e., recognition, involves two main methods: global sign recognition (holistic) and single digit recognition. In the global sign recognition approach, the recognition of SLS is performed for the entire candidate sign. While digit-based techniques extract one or more digits to recognize the speed number, instead of classifying the whole sign as a single entity.

In this paper, North-American SLS detection and recognition system is explored. More precisely, we focus on four categories of SLS used in North America: white, nighttime black, advisory, and working zone orange signs, see Figure 1. Contrary to the existing detection approaches based on shape or color, the detection phase of our suggested system is based on gradient information. Hence, two-level Histogram of Oriented Gradients (HOG) [3] and Support Vectors Machine (SVM) [5] classifier are used for detection and recognition of SLS.

Fig. 1. Samples of the four rectangular speed limit signs categories considered in our work. From left to right: white signs, advisory yellow signs, working zone orange signs and nighttime black signs

Our contributions are listed as follows: 1) the construction of new database for North-American SLS, called NASLS, which regroup the four main categories (i.e., white, black, yellow and orange signs); 2) the exploitation of the HOG features as a detector for SLS; and 3) the detection and recognition of four categories of SLS instead of only one as in the majority of papers.

This paper is structured as follows. In Section II, we introduce some characteristics of the North-American SLS used in this paper. After that in Section III, an interesting review of the detection and recognition of SLS systems is presented. As our detection system is based on HOG, we present in Section IV some aspects and parameters of HOG used in our experiments. The recognition module is based on SVM-classifier, and it is explained in Section V. Then, we present in Section VI the main architecture used in this paper. Our database and some experimentation results are presented in Section VII and VIII, respectively. Finally, we conclude our work in Section IX.

II. SLS CHARACTERISTICS

Speed Limit traffic Signs (SLS) are used to regulate the speed of vehicles and motorcycles in downtown and highways, and hence protect drivers and pedestrians against dangerous situations. Contrary to the circular European SLS, North American SLS have a rectangular shape. The North-American SLS expresses numerals and lettering on a white, yellow, black and orange backgrounds with a black border. While European SLS express circular white signs with a red circular border, see Figure 2. As previously stated, in this paper, we focus on North-American SLS. The Canadian SLS usually use MAXIMUM XX to indicate that XX is the maximum authorized speed, while the American SLS use SPEED XX. Canadian SLS are expressed in kilometers per hour (km/h) since 1977, while American SLS are still displayed in miles per hour (mph).

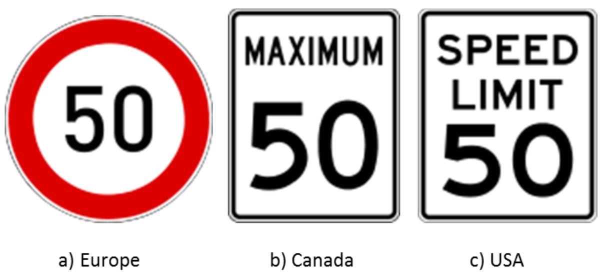

Fig. 2. European vs. North American Speed Limit Traffic Signs

As stated in [1], two types of SLS are used in North-America: the first type concerns the SLS designated to normal vehicles (passenger-car) including minimum SLS and black nighttime SLS. The second type are SLS designated for other type of vehicles such as trucks. In this paper, these types are classified in four categories regarding their colors: white, black, yellow and orange signs.

III. RELATED WORKS

A. Detection

The first step of the recognition process is sign detection. In some signs detection and recognition systems, the detection is preceded by a pre-processing stage. The fundamental function of the pre-processing stage is to enhance the input image, which allows minimizing the false positive detection. The detection stage allows extracting ROIs from the pre-processed image. Two basic approaches are used to detect SLS: detection through colour and shape. We review only research works dedicated to speed limit traffic signs.

1) Colour-based algorithms: Colour-based detection methods aim to segment the colours of SLS in order to provide ROIs for classification stage. Colour-based approach is usually used to detect color of SLS (e.g., red, yellow or blue), see Figure 3. Different colour spaces are used to separate the speed limit sign from the background. The selection of the appropriate colour space is important, since it affects the result of the detection. For instance, authors in [15], [17] used the YCrCb color space, while in [7] and [8] the RGB color space is preferred. Detection of SLS is not frequently based on color as with other traffic signs. That is, only few works are found in the literature.

Fig. 3. Examples of colored SLS

Color-based segmentation algorithm is performed to extract, for example, the red color of speed limit signs. For instance in [7] and [8], an image filtering algorithm is used to emphasize the red circle of the sign(s), where the authors use thresholding segmentation. Color segmentation is either performed alone to detect red color as in [7], or followed by a shape detection algorithm to select only the rectangular or circular forms, and reject other undesirable red objects as in [15], [17]. More precisely, in [15] after color thresholding, the authors use the RANSAC algorithm [2] to detect the shape of SLS, i.e., circle silhouette, while in [17] the Hierarchical Hough Transform is preferred.

2) Shape-based algorithms: Shape is effectively used to detect SLS, especially for North-American SLS, where colour-based techniques might fail. Shape-based algorithms start by extracting features representations of images to generate feature map. After that, ROIs containing SLS are processed in next stages.

Image features can be found using edge detection techniques such as Sobel or Canny filters. After edge detection, edge linking techniques (e.g. the Hough Transform) are usually applied to detect SLS. An interesting work is suggested in [9], where the authors present a modular system applied to both American and European speed limit signs. The authors develop two different detection modules for the two shapes circular and rectangular. That is, a circular Hough-transform (HT) is adapted to the circular European SLS, and rectangular edge detection is developed to the U.S. SLS.

Fast Radial Symmetry, a variant of circular HT, is a simple efficient method to detect SLS signs. It is based on the symmetric nature of circular or rectangular shapes. However, this method might fail when images contain many edges. In [16], authors show that the radial symmetry detector can be combined with cross-correlation technique to classify circular SLS signs in real time. The detection is based on a fast radial symmetry method, where each non-zero gradient element votes for a potential circle centre. The radial symmetry detector is run over a total of 1107 frames from the camera. From this sequence 152 signs are detected (90%). To detect rectangular pattern from video, a modified version of the radial symmetric transform presented in [16] is used in [12]. To remove a non-speed signs object from the previously detected rectangular shapes, a classifier based on Viola-Jones method is used. A fairly new method for speed limit signs recognition is suggested in [19], where authors use a rectangle detector based on [12] to look for a rectangle candidates. More recently, a GPU-based radial symmetry detector of [16] is implemented in [14] to detect European speed-limit signs. The detection process starts with a preprocessing stage consisting in edge detection and gradient computing. To detect the potential circle center of SLS, a voting procedure is performed based on a radial symmetry method. The coordinates of the SLS center are then used to separate the ROIs from the image. The authors in [13] present a system to recognize circular speed limit signs. The detection stage starts by detecting edges based on image gradients. After that, a noise removing task is investigated using HOG. Finally, Fast Radial Symmetry Transform is used to detect circular signs.

B. Recognition

In this phase, the classification of the selected ROIs is performed to identify the exact speed limit, or reject the ROI. Following the reviewed literature, the recognition methods for SLS are divided into two categories: the holistic approach and digit-based approach, see Figure 4. In the holistic approach, the recognition of SLS is performed for the entire candidate sign. While Digit-based techniques extract one, two or three digits to recognize the speed number, instead of classifying the whole sign as a single entity.

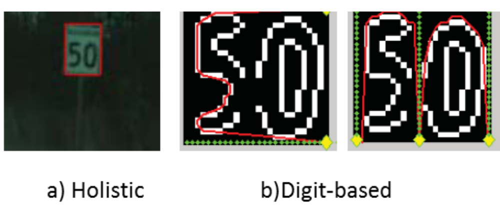

Fig. 4. Holistic vs. Digit-based recognition approaches [19]

1) Holistic approach: The majority of published papers on SLS recognition have followed a holistic technique. Mainly, SLS are recognized using learning-based techniques, such as Neural Network (NN), Support Vector Machine (SVM), or template matching algorithms. The choice of the appropriate recognition algorithm depends essentially on the training samples statistics, the features used and the output of the detection algorithm. To recognize the whole SLSs in [15], two steps are performed, a normalization step followed by a NN classification step. Normalization ensures that only the white interior of the sign is delivered to the NN. A feed-forward multi-layer perception network is used to train the following signs types from 10 to 100km/h. The network consists of 400 neurons in the input layer, 30 neurons in hidden layer and 12 neuron outputs. In their tests, the authors consider database of 101 images, for which a 97% of signs are detected.

To recognize SLS in [17], four NN (MLP, RBF, LVQ and Hopfield) are trained by only 66 images SLS (10-110). The authors show that the MLP network yields the best results.

The SVM (see Section V) can also be used to recognize the whole pattern containing speed-limit. For example the authors in [13] use the SVM with binary tree architecture to identify categories of signs. The recognition stage in [11] starts by correcting the angle rotation of candidates SLS and segmenting the speed limit number. Then, the segmented numbers are classified based on binary tree of linear SVM.

After the detection stage in [12], remaining candidates go through recognition stage. This stage starts by sign alignments operations such as rotation and resizing to get an accurately aligned images. Then, Vector Features are generated via linear discriminant analysis. After that, the normal distribution classifier is applied to recognize speed limit signs. As soon as the speed limit is classified, the final recognition result is performed within a temporal information propagation framework.

At the recognition stage in [16], a normalized cross-correlation from the Intel Integrated Performance Primatives library is used. The authors form a total of eight templates for each speed limit sign. From 126 valid candidates 96% are correctly classified. The disadvantage of their system is that only 75% of the signs returned as candidates are correctly classified.

2) Digit-based approach: Contrary to the previous holistic approaches, Digit-based techniques extract one or more digits to identify the number inside the SLS, instead of classifying the whole candidate as a single object. For instance in [7], only the first digit of the total number is used to recognize the speed limit (since the second digit of the speed number is always zero). This restricts the application of this algorithm to only SLSs ending by 0. Other Signs containing numbers can be confused, see Figure 5. To classify the extracted number, a NN trained by the back-propagation algorithm is used. The network consists of 35 inputs (7 x 5 bit array), 35 hidden units and 6 outputs. The authors use a very limited database which contains only 198 images.

Fig. 5. Traffic signs like SLS

A connected-component labeling methods are applied to segment digits for both circular and rectangular candidates in [9], instead of classifying the whole candidate as a single sign. The segmented digits are then classified using the multilayer perceptron NN called optical digit recognition (ODR) for European signs. The European digits database used by the authors contains 2762 digits examples and 2789 negative examples. For the American SLS, another classifier is used.

In fact in [9], the connected-component labeling method used to segment digits fails when two digits touch each other on the binary image. This results in non-recognition of the speed limit sign. That is, an improved digit character segmentation is suggested in [10] for only European SLS, and it consists in two steps: 1) Find the numerals and lettering inside the circular sign; 2) Segment digits into the obtained rectangular zone. This improved version significantly improves the correct detection rate with 94 % global correct sign detection rate on French and German roads. This approach brings 9% increase in detection rate, compared to [9].

To obtain potential digits from rectangle candidate, the authors of [19] suggest an improved version of Stroke Width Transform (SWT) [18], which they call Improved SWT (ISWT)[1]. The ISWT is used to segment digits inside speed limit areas, and yields an image where each pixel contains the width of the most likely stroke it belongs to. After this step, a modified Connected-Component labeling is used to group these pixels into digit candidates. To make each digit candidate contains only one number, a two-stage segmentation method is used: 1) finding upper/lower limits of the digit candidate and 2) determining left/right limits of the digit candidate. To recognize digits, a Support Vector Machine using Majority Voting strategy is used. Finally, combinations of recognized digits are verified whether are speed limits or not. The authors test their system in different conditions using more than 200 training samples. The correct recognition rate is more than 96%.

IV. HOG-BASED DETECTION SYSTEM

Gradient information has been successfully used to detect traffic signs. Its purpose is to describe an image by a set of histograms of gradients. Histograms of Oriented Gradients (HOG) [3] is an example of such gradient-based methods. The first step is to convert the original image into grayscale image. After dividing the image into a set of overlapping blocks, HOG divides each block into a set of non-overlapping cells. For each cell, a histogram of the gradients orientations is performed. To classify the generated features, a classifier based on SVM is used. HOG has been successfully applied for SLS detection in several works like [4]. The histograms of oriented gradient is computed by calculating gradients and building histograms. After that, the histogram is normalized. These steps are explained as follows. First, several masks are tested to compute gradients. The best of them [1 0 1] is used. For color images, for each color channel, separate gradients are calculated. The gradient with the largest norm is taken as the pixel's gradient vector. To increase the performance of the descriptor, unsigned gradients which value goes from 0 to 180° are considered.

After that, the image is divided into a set of cells of size 8×8 pixels. For each cell, the histogram of gradient (9 orientation bins) is computed for later use as descriptor blocks. This is performed by accumulating votes into bins for each orientation. The vote is weighted by the magnitude of a gradient at the pixel to get a best result as stated in [3]. Finally, when all histograms are computed, the descriptor vector is built in a single vector, and cells histograms are normalized. For normalization purpose, cells histograms are organized into blocks of size 16×16 pixels. The normalization factor is computed over the block using L_2 norm. Once this normalization step has been performed, all the histograms can be concatenated in a single feature vector.

[1]A stroke is defined as a contiguous part of an image that forms a region of a constant width [18].

V. SVM CLASSIFIER

After the generation of descriptors in Section IV, a recognition based on SVM step is performed. A short reminder about SVM theory is given as follows. It looks for an optimal hyperplane as a decision function in a multi-dimensional space to separate between classes. Given a training set of instance-label pairs $(x_k; y_k)$; where $x_k \in R^n$ are the training examples, and $y_k \in \{-1, 1\}$ the class label. The SVM consists in mapping x_k into a high dimensional space by the function ψ. After that, it finds a linear separating hyperplane of the forme: $w.\psi(x) + b = 0$ with the maximal margin in this higher dimensional space. In the case of L_2 soft-margin SVM classifier, the optimization problem is given as follows [5]:

$$min_{w,\xi} \frac{1}{2}\|w\|^2 + C\sum_{k=1}^{m} \xi_k \tag{1}$$

subject to: $y_k(w.\psi(x_k) + b) \geq 1 - \xi_k$, $\xi_k \geq 0$, $\forall k$

where $C > 0$ is the penalty parameter of the error term. The solution of this problem is obtained using the Lagrangian theory.

It is shown in [5] that the vector w is of the form:

$$w = \sum_{k=1}^{m} \alpha_k^* y_k \psi(x_k) \tag{2}$$

where α^* is the solution of the following quadratic optimization problem:

$$max_\alpha W(\alpha) = \sum_{k=1}^{m} \alpha_k - \frac{1}{2}\sum_{k,l}^{m} \alpha_k \alpha_l y_k y_l K(x_k, x_l) \tag{3}$$

under the constraint: $\forall k$, $\sum_{k=1}^{m} y_k \alpha_k = 0$, and $0 \leq \alpha_k \leq C$. Note that the solution of the SVM problem depends only on the kernel function $K(x_k, x_l)$, which is in our case a linear function.

We use *SVMlight* [6], an optimized version of SVM, to generate the classifiers based on the feature vectors extracted from HOG. There are two modules of *SVMLight*, one for constructing the hyperplane on the input data, i.e. svm_learn; another is for generating the predictions based on the learned classifier, i.e. $svm\_classify$. We use linear function with default parameters to train the classifier. After that, we use $svm\_classify$ to test our model based on the NASLS (test dataset).

VI. Architecture design

Two levels of SVM-based classifiers are investigated. We use the first classifier to detect all rectangular SLSs. Then, the second classifier is used to recognize a specific speed limit, see Figure 6. The first classifier is applied to the entire region of the image to be detected. It is used to get the regions of interest that may contain traffic signs. It is trained using the following method. We use HOG descriptors extracted from the positive data set to train this first SVM classifier in order to recognize all suspecting traffic sign areas. The positive images in the data set are represented by all speed limit signs including white (e.g., 50 km/h), night time black (e.g., 60 km/h), orange working areas (e.g., 50 km/h), and advisory yellow signs (e.g., 40 km/h), see Figure 1. On the other hand, negative images are the patches cropped from pictures without speed signs.

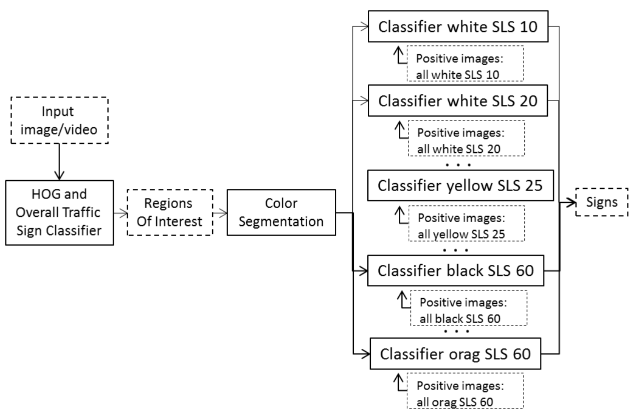

Fig. 6. Architecture design

The second classifier is used to recognize the exact traffic sign from the ROIs extracted by the first classifier, i.e, a set of rectangular shapes. We use HOG descriptors to train a linear SVM classifier for each SLS, for example white SLS 50 km/h. In this case, the positive images should only contain the traffic sign that we want to recognize. While other speed signs are regarded as the negative data set. Let us consider the case concerning the detection of white SLS ranging from 10 to 100 km/h. The positive images used by the first classifier should be 10 to 100 km/h, while the negative samples are the image patches without traffic signs.

From our experiments, we remark that the differentiation between SLS having the same number (e.g., 40km/h) and different colors (white and yellow) at the recognition stage could be problematic, for instance white 40 km/h and yellow 40 km/h. To distinguish between SLS having the same number and different colors we suggest to process yellow signs independently as follows. We added, before the recognition stage, a color estimation step which is explained as follows. When the ROI is carried out, we extract its middle part called ROIc, which possibly contains black numbers and the desired unknown color of the sign. Our aim is to eliminate black numbers in order to avoid their influence on the decision of the color of the rest of ROIc. To eliminate black numbers from ROIc, the red channel is extracted, since the red channel value of black color is smaller than that one of yellow and white colors. After the elimination of black pixels from ROIc, we extract the value of blue channel for each ROIc. The average value of blue channel is calculated in order to determine whether the color of ROIc is yellow or white. If the blue value is high, the SLS color is white, otherwise it is yellow. After the color estimation step, the yellow and white will be separated automatically.

For the black speed limit signs, the white classifiers are not able to detect and recognize them. The grey scale images of black and white signs are totally different, so the calculated oriented gradients cannot be used to perform the match. Hence, we need to train a black classifier specifically.

VII. Database creation

Our database of North-American SLS (NASLS) is created from a set of images and videos collected mainly from Canadian roads. and some images from Internet. These videos are collected at different daytime and under various conditions using Sony camera Full HD 1920×1080 pixels. It is often updated by adding new signs. We collect, annotate and align images manually. The size of the traffic signs are normalized to vary from 25×25 to 650×650 pixels, Figure 7 . Each image contains a margin around the speed limit sign, which allows for the usage of edge detectors. The first version of NASLS database contains mainly training set (positive and negative) and testing set. The negative training samples contain 6115 images without speed limit sign, while positive training samples contain 941 images of SLS. As aforementioned, four main SLS categories are used in the positive training set of NASLS database, including white, black, yellow and orange signs. Each category is supposed to contain a range of specific speed values called classes. The white category contains 10 classes represented by the signs 10, 20, 30, 40, 50, 60, 70, 80, 90 and 100 km/h. The black nighttime signs category contains 4 classes 35, 45, 60 and 65 km/h. The yellow advisory signs category contains 7 classes 25, 30, 35, 40, 45, 50 and 65 km/h; and the orange working areas signs category contains 3 classes 25, 50, and 80 km/h. We highlight that our database is in construction and often updated by adding new signs and new classes.

Figure 7 and Figure 8 show some positive training samples, and negative samples. We use more than 2364 frames as testing data different than training set and do not contain any training image.

VIII. Experiment results

To evaluate the performance of our system, a set of videos are used. We resize the positive training images to 50×50 pixels, and we use the center area of size 40×40 pixels to calculate the HOG feature vector. This allows to leave a rectangular margin around the SLS to calculate the gradients of the edge. As aforementioned, two classifiers are trained: the first classifier and the second classifier.

Fig. 7. Positive training samples

Fig. 8. Negative training samples

The dataset used to train the first classifier is:

- Positive images: 6 classes of SLS in NASLS training dataset.
- Negative images: randomly selected images from the negative images in NASLS dataset.

The dataset used to train each second classifier is:

- Positive images: specific speed limit sign from NASLS, for instance white speed limit 40 as previously explained.
- Negative images: all other images from NASLS dataset (including white 10-30 and 50-100) and video clips capture along the roadside.

We use two metrics to evaluate the performance of our system: the True Positive Rate (*tpr*) and the Positive Predictive Value (*ppv*) defined as follows:

$$tpr = \frac{tp}{p} \times 100\% \tag{4}$$

$$ppv = \frac{tp}{tp + fp} \times 100\% \tag{5}$$

where *tp*, *p* and *fp* stand for number of true positives detected, number of total positive images and number of false positive detected respectively.

Based on the predictions from the first and second classifiers, we compute the overall *tpr* and *ppv*. Let us consider the evaluation of testing the white speed sign 50. To compute the overall *tpr*, we use the *tp* from the second classifier as the overall *tp* and the total number of sign 50 as the overall *p*. We do not directly use the input positive number of the second classifier as the overall *p*, since there are may be some positives missed by the first classifier. To calculate the overall *ppv*, we use the *tp* and *fp* from the second classifier as the overall *tp* and the overall *fp* respectively. The testing results, i.e., predictions, are then drawn using Matlab.

We tested almost all speed limit signs, and we choose three typical graphs of the detection, and some statistics related to the recognition stage in Table I to present here. We can conclude from Figure 9 and 12 that under a high *ppv* value, i.e., low false positive rate, the *tpr*, i.e., recognition/detection rate, is very high. For example, for speed white limit sign 50 the detection rate is around 96% for *ppv* = 95.

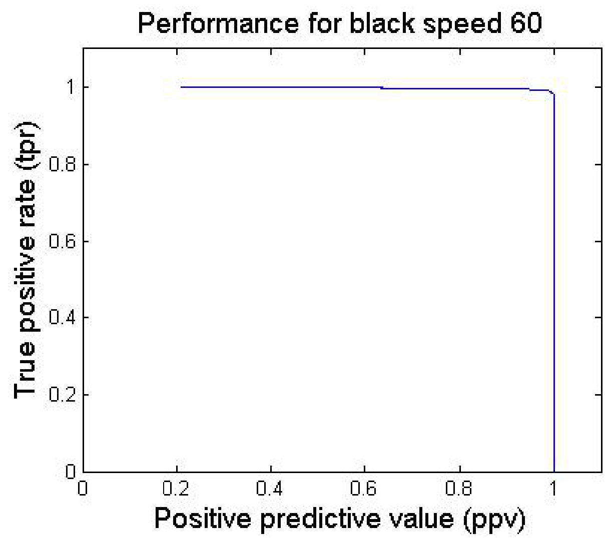

Fig. 9. Detection result as a function of ppv value for black SLS 60 km/h

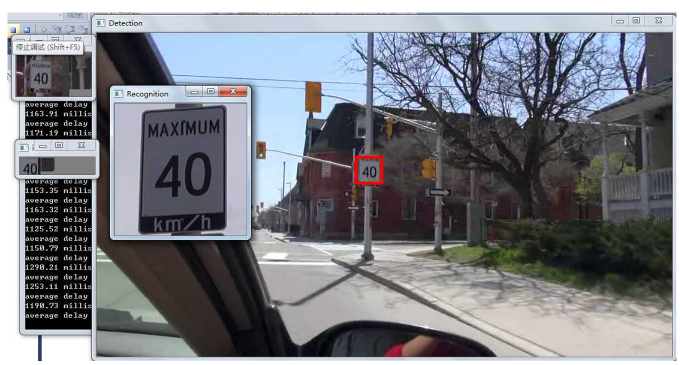

Fig. 10. Example of detected and recognized white SLS 40 km/h in sunny conditions in Ottawa streets

Figures 10 to 14 show the detection and recognition of the four signs categories considered in this paper. From Table I, the recognition rate of all signs categories, is usually higher than 94% except for orange SLS signs. The reason behind the low rate detection of orange SLS is the presence of orange-

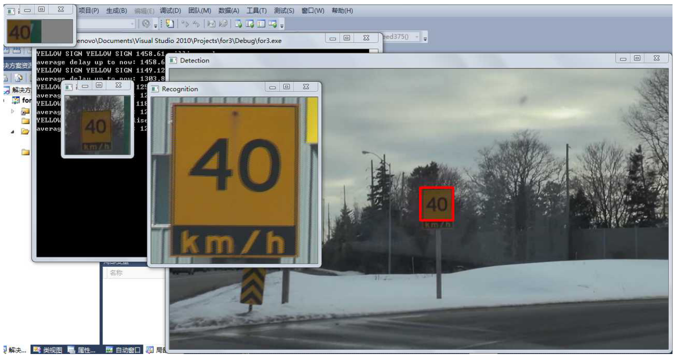

Fig. 11. Example of detected and recognized yellow SLS 40 km/h in snowy conditions in Ottawa streets

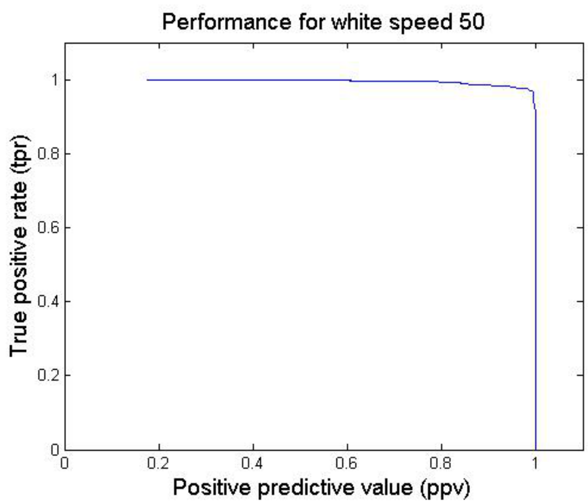

Fig. 12. Detection result as a function of ppv value for white SLS 50 km/h

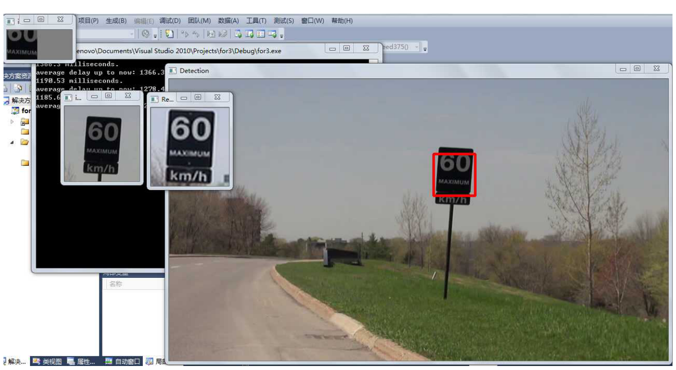

Fig. 13. Example of detected and recognized black SLS 60 km/h in cloudy conditions in Ottawa streets

Fig. 14. Example of detected and recognized orange SLS 50 km/h in sunny conditions in Ottawa streets

TABLE I
RECOGNITION RESULTS

Categ.	Class	dataset	Recog.	incorrect	Recog. (%)
White	40	6069	5935	134	97.79
	50	4962	4688	274	94.48
Yellow	40	2933	2876	57	98.06
	50	2877	2808	69	97.60
Black	60	1349	1339	10	99.26
Orange	50	1248	1126	122	90.22

like background in streets, which increase the false recognition ratio, and decrease the whole recognition of orange signs.

IX. CONCLUSION

A North-American speed limit signs detection and recognition system is presented along this paper. Contrary to the existing recognition systems, four categories of SLS used in North of America are considered: white signs, nighttime black signs, advisory signs, and working zone orange signs. Hence, a new online database of North-American SLS, called NASLS, which regroup the four main categories, is constructed. To detect signs, gradient information is used. We adapt HOG to our detection stage. Contrary to the existing detection approaches based on shape or color, the detection phase of our suggested system is based on gradient information. Hence, two-level HOG and SVM classifier are used for detection and recognition of SLS. We show through an extensive set of experiments that our system achieves an average accuracy of more than 94% of SLS recognition.

ACKNOWLEDGMENT

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