

# Road Sign Tracking with a Predictive Filter Solution

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**Abstract**—This paper deals with the problem of estimating traffic sign position in successive frames for automatic detection systems, whose main applications involve road sign maintenance and driver-assistance systems. For road sign detection systems, the problem is traditionally handled using the information in a single-frame way. In this paper we describe the application of adaptive filters for tracking road signs. Results show that using a predictive filter we get a better performance than the obtained at the output of the recognition system, processing each frame independently. False alarms are eliminated, in most cases, because they are temporally incoherent.

## I. INTRODUCTION

Traffic signs are crucial for driver's safety and their objective is to guide, warn and regulate traffic. They supply information to help drivers and pedestrians in such a way as to enhance traffic safety. For this reason, automatic road sign detection systems has been an important issue for research recently because drivers may not notice the presence of road signs. Problems of visibility come from the bad conservation of the signs, occlusions, etc.

Road signs present particular colors and shapes to attract driver's attention and both characteristics: color and geometric shape, determine the content of traffic signs. However, the automatic detection of a traffic sign involves the same difficulties as object recognition in natural outdoor environments:

- 1) Lighting conditions are changeable, according to the time of the day, weather conditions, etc.
- 2) The presence of other objects in the scene can occlude partially the visibility of a sign and produce shadows.
- 3) The sign's appearance can change because there are variations respect to size, visibility angle and position in the image.
- 4) The long exposure to the sunlight provokes that the paint of traffic signs often gradually fades.

Most efforts during the past few years have focused on the development of computational algorithms to detect road signs in each independent frame. Many works divide the algorithms into two stages, detection and recognition. There are two main approximations to detect traffic signs: those based on color criteria ([1],[2],[3],[4],[5]) and those that employ a border detection ([6],[7]). At recognition stage there are many solutions, such as techniques based on different Neuronal Networks ([8],[9],[10]), Support Vector Machines (SVM) [11] and genetic algorithms [12], where no tracking technique is

used to improve the performance. However, the independent analysis per frame makes wasting the inter-frame information.

Road sign detection systems such as driver assistance systems and those used to evaluate the signalling of the road for maintenance purposes require detailed knowledge of the sign with the additional purpose to reduce false alarms. This idea is oriented to reduce false alarms in scenes where objects with color and geometric shape so similar to signs appear.

The detection of road signs using only a single image has two problems: 1) the correctness of road signs is hard to verify; and 2) it is difficult to detect correctly a traffic sign when temporary occlusion occurs, as is illustrated in Fig.1. Although some researchers consider that tracking task reduce the search space and time, we believe it is not true in a multiple object tracking system. In fact, new traffic signs can appear in a scene and a new track process will be initiated even though other signs are being tracked simultaneously. By using a video sequence, we preserve information from the preceding images, such as the number of detections of road signs and their corresponding sizes and positions projected in the image. This information increases the accuracy of road sign detection in subsequent images. Moreover, information supplied by later images is used to assist in the verification of detection of traffic signs, so that detected and tracked objects that are not road signs can be eliminated as soon as possible. Thus, using inter-frame information the amount of false alarms will be reduced and we will manage more valuable information for road sign detection than using single images.

Recently, a complete system to detect traffic signs including a tracking algorithm is presented in [8], with three important limitations: a) the physical sizes of signs must be known, b) the speed of the vehicle must be constant and known, and c) the algorithm assumes straight trajectories. In the mentioned work, both the prediction of the radius of the road sign in the image and the position of the sign (vertical and horizontal coordinates) in the image plane are estimated.

This paper is organised as follows: section II presents a short description of our system to detect and recognize road signs, section III presents a description of the proposed tracking algorithm, section IV report the obtained results under different conditions, and section V summarizes and concludes the paper.



Fig. 1. Example of a traffic sign occluded partially in a video sequence.

## II. DETECTION AND RECOGNITION SYSTEM

Our whole system to detect road signs automatically is described exhaustively in [11] and results from it can be found at <http://roadanalysis.uah.es/Documentos/Results>. It allows us to extract possible signs from the image, and classify the candidate objects into specific type categories such as speed limit or stop. The system consists of the following steps:

- Segmentation
- Shape classification
- Recognition

### A. Segmentation

Color information is considered to extract candidate objects from the input image by thresholding. For this purpose, HSI color space is employed for chromatic signs. The advantage of this color model is that two components (Hue and Saturation) encode the color information, being strongly robust against lighting conditions variations. At the same time, white signs are detected with the help of an achromatic decomposition in a similar way that in [13]. Then, a connected-component operator is applied to label the interesting objects. Most common road signs present a red rim and an inner white region. This characteristic led us to consider the sign as a possible sum of two contributions corresponding to their chromatic and achromatic segmentation masks (see Fig.2) where both parts are processed independently in the complete system. The advantage of this idea is that a sign can be detected by different colors. Obviously, some limits can be imposed respect to the size or aspect ratio. In other words, small regions or big regions are eliminated.

### B. Shape classification

All objects from the segmentation are classified in this stage using linear SVM to classify the feature vectors (in our case, Distance to Borders vectors). The Distance to Borders vectors (DtB) represent the distances of each contour of the object's bounding box to the corresponding borders of the candidate object. According to the color which has been used in the segmentation, only some given shapes can be expected. For

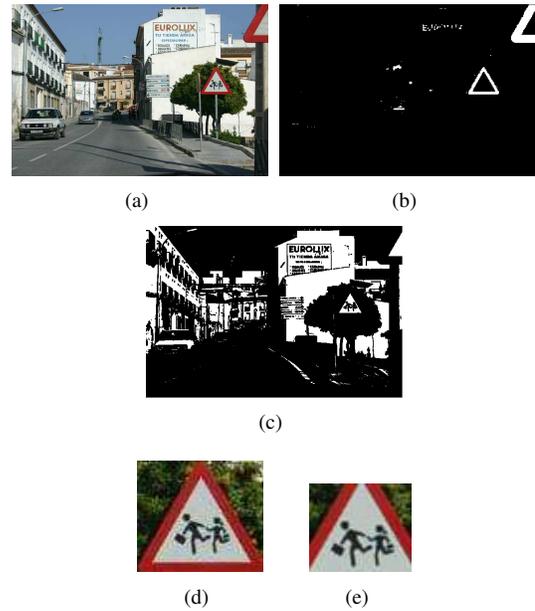


Fig. 2. Example of a traffic sign occluded partially in a sequence video. (a) Original image; (b) segmentation mask by red; (c) segmentation mask by achromatic decomposition; (d) traffic sign detected by red contour; (e) traffic sign detected by white inner area.

example, objects segmented using red clues will be circular, triangular or octagonal. Before classification step, all objects are oriented in a reference position and thus, the evolution of the geometric shape-vectors is so similar in most cases.

### C. Recognition

This step is implemented by SVM with gaussian kernel where the input vector is a block of 31 x 31 pixels in gray-scale image for each candidate blob. Thus, the interior of the object is normalized to these dimensions. In order to reduce the dimensions of feature vectors, only those pixels that must be part of the sign (pixels of interest) are computed. Different one-vs-all SVM classifiers with a gaussian kernel are used so that the system can recognize every sign. Both the training and test are done according to the color and shape of each candidate region. Thus, every object is only compared to those signs that have the same color and geometric properties than the blob to identify.

The amount of training samples per class varies between 20 and 100. We use an average of 50 training patterns for each class, but only some of them define the decision hyperplane as support vectors. Of course, in the training set are included samples of noisy objects that could be confused with traffic signs by this recognition module. Searching for the decision region, all feature vectors of a specific class are grouped together against all vectors corresponding to the rest of classes (including here noisy objects). Due to the size normalization of each blob the method is invariant to scale changes and, on the other hand, since all interesting objects are oriented in a reference position we can conclude that the system is strongly robust to habitual rotations of road signs. The results for two video sequences using a single-frame detection are illustrated

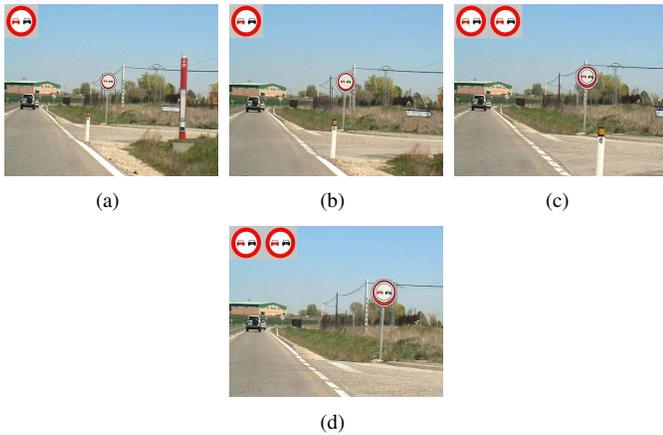


Fig. 3. Experimental results of a video sequence S1.

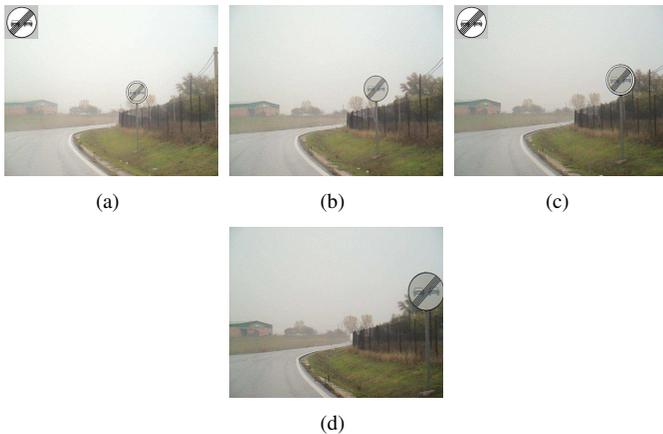


Fig. 4. Experimental results of a video sequence S2. Examples of recognition process including miss detection in (b,c).

in Fig.3-4. In Fig. 4 we can see a sequence in which the sign is not detected in some frames due to difficult segmentation to isolate the sign from the sky.

### III. ROAD SIGN TRACKING

Recognition and tracking objects with a CCD camera is a non trivial problem because there exist relative motion between the camera, the static objects (in our case, traffic signs) and the environment. On the other hand, the system has to be able of tracking many targets simultaneously. As we move toward traffic signs, we can see the signs, from a camera point view, as a dynamic system whose behaviour can be estimated by a cinematic model and using smoothing and prediction filters we can estimate sign parameters between successive frames of a sequence. To this end, the Kalman filter [14] and the Alpha-Beta-Gamma ( $\alpha - \beta - \gamma$ ) filter [15], as a special case of the previous one, are a fundamental tool. In most cases, the relative movement of the sign respect to the driver is lineal except in cases such as curve sections of the road and lateral displacements of our vehicle.

#### A. Algorithm Description

Once the system recognizes a traffic sign in the incoming frame, two options are possible. If there is no correspondence between the new object and the previous ones, a new track process is initiated. Otherwise, the track data structure which contains the objects to track is updated regarding to the new information. This ensures that sequential detections from the same object are processed together to estimate the object's parameters. It is important to point out that, at least, two detections are required to consider the object as a traffic sign.

Information such as position coordinates, size, color, type category and the mean gray level of the region occupied by the object comprise, in our case, the components of the track process and are recorded as the object's signature. The tracking system must decide whether each candidate blob from the actual frame belongs to a new object or belongs to an object that has been detected in earlier frames of the sequence. And in order to accomplish this task, the tracking module uses association algorithms based on the signature's features. In other words, in this process each new detection is compared with all previous objects to avoid establishing redundant tracks according to:

- Segmentation color: red, blue, yellow and white. To establish a correspondence between two objects, both candidate objects must be detected by the same color, except in cases of signs with white inner area and red contour.
- Geometric shape: triangular, circular and rectangular. To associate a new object to an old tracked object, both objects must present the same shape.
- Bi-dimensional X-Y coordinates: the location of a new traffic sign must be near to the predicted position for a previous detected object to they can be associated.
- Aspect ratio: the aspect ratio of each sign is approximately invariant during all the video sequence.
- Dimensions of the blob: the dimensions of each object are larger as we move toward it.
- Mean gray-level: it is approximately constant for each object in a sequence under daylight.

All observations whose position error, defined as the difference between the real position and the predicted position of a given track, are less than the a maximum threshold are associated to that track. For each new object not associated to a previous one, a new track process is established accordingly. Since new objects are compared to all existing track process, a matrix defines the association between the new detections and all existing track process. In cases where a new observation is associated to more than one track process, a criterion based on the euclidean distance between the new object's position and the predicted position of all existing track objects is utilized so that establish a single tracking.

The goal of this work is to study how the proposed algorithm based on probabilistic prediction techniques is able of tracking traffic signs. The steps to use a predictive filter for vision tracking are:

- 1) **Initialization.** In this step objects of interest are looked

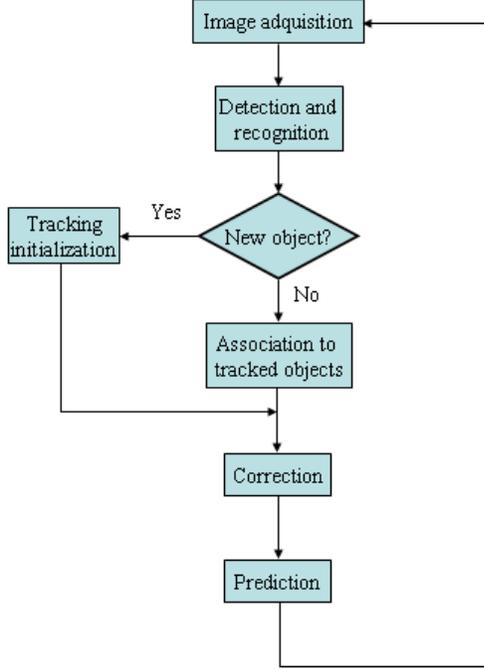


Fig. 5. The dynamic detection algorithm.

for in the whole image due to we do not know the objects' position. It is important to point out that some researchers reduce the looking zone in order to decrease the computation time. Nevertheless, traffic signs do not appear always in the usual position (i.e. lateral margin of the road) and our system must be invariant to possible shifts.

- 2) **Prediction.** In this stage the predictive filter estimates the position of the object at time  $t+1$ , that in our case is given by the two points that define the rectangle bounding-box of the object.
- 3) **Correction.** In this part the system of detection and recognition detects the candidate objects (which should be in the neighborhood of predicted points in the previous stage) and we use their real position (measurement) to carry out the state correction.

The steps 2 y 3 are carried out while there are candidate traffic signs to track. At this point, we have to explain that when a traffic sign is not verified in 5 consecutive frames, we suppose the sign has been overcome and, in conclusion, the candidate object leaves the tracking structure.

Several cases may happen while the system processes a video sequence. When a new object is detected while there is no corresponding object in the past, it may alert a new traffic sign is present in the field of view. If this new region can be tracked successfully for several frames, it will then be considered as a new sign with a unique label assigned and a predictive filter is initialized to track this new road sign in the ensuing frames. A simplified block diagram of the proposed algorithm is shown in 5.

Since a interesting object can be identified with different class types by the recognition module in a video sequence, we define a criterion to assign the final type to each sign using a weighting function. Thus, the weight associated to each possible  $i$ -class is given by:

$$K_i = \frac{N_i}{1 + \sum_k D_k^2} \quad (1)$$

where,  $N_i$  defines how many times the object is identified with  $i$ -class in the sequence and  $D_k$  represents the distance between the index of each frame of the sequence in which the object is assigned to  $i$ -class and the index of the last frame of the sequence. The summatory function of distances in the denominator considers the fact that the recognition process is always more accurate in the final images than in the first ones of a sequence, except in cases of partial occlusion.

### B. Object Tracking

The  $\alpha - \beta - \gamma$  filter is used in this work to model the relative motion between the camera and the road-sign in the scene. The Kalman filter works in two stages: prediction and correction and in our case, the state vector include position, velocity, and acceleration. Suppose that the two points that define the rectangle bounding-box that inscribe the traffic sign are described as  $\mathbf{p}_1(t)$  and  $\mathbf{p}_2(t)$ , where for each point  $\mathbf{p}(t) = [x(t), y(t)]^T$ . The state vector for each point is  $\mathbf{x}(t) = [\mathbf{p}(t), \dot{\mathbf{p}}(t), \ddot{\mathbf{p}}(t)]^T$  where  $\mathbf{p}(t)$  represents the position,  $\dot{\mathbf{p}}(t)$  the velocity and  $\ddot{\mathbf{p}}(t)$  the acceleration of each one of the two corresponding points that define the tracked object. By using Taylor series expansion, the state prediction equation is:

$$\mathbf{x}(t^-) = \mathbf{A} \mathbf{x}(t - \Delta t) + \mathbf{w}(t) \quad (2)$$

$$\begin{bmatrix} \mathbf{p}(t^-) \\ \dot{\mathbf{p}}(t^-) \\ \ddot{\mathbf{p}}(t^-) \end{bmatrix} = \begin{bmatrix} \mathbf{I}_2 & \Delta t \mathbf{I}_2 & \frac{\Delta t^2}{2} \mathbf{I}_2 \\ \mathbf{O}_2 & \mathbf{I}_2 & \Delta t \mathbf{I}_2 \\ \mathbf{O}_2 & \mathbf{O}_2 & \mathbf{I}_2 \end{bmatrix} \begin{bmatrix} \mathbf{p}(t - \Delta t) \\ \dot{\mathbf{p}}(t - \Delta t) \\ \ddot{\mathbf{p}}(t - \Delta t) \end{bmatrix} + \mathbf{w}(t)$$

where  $\mathbf{I}_2$  and  $\mathbf{O}_2$  represent  $2 \times 2$  identity and null matrices, respectively. The relation between the state vector in times:  $t^-$  and  $(t - \Delta t)$  is given by a  $3 \times 3$  matrix known as the transition matrix,  $\mathbf{A}$ . The vector  $\mathbf{w}(t)$  represents the model prediction uncertainty, and it is assumed to be a random variable with a zero mean and a covariance matrix  $\mathbf{Q}(t) = E[\mathbf{w}(t)\mathbf{w}^T(t)]$ .

In the prediction stage, the sign position is computed by extrapolating the state of the Kalman filter from the previous frame to the current frame. Then the correspondence between the predicted object position and the object position detected by our recognition system is computed. We estimate the sign's position, and velocity and acceleration of the relative motion by evaluating the difference from the corresponding trajectory:

$$\mathbf{z}(t) = \mathbf{H}\mathbf{x}(t) + \mathbf{v}(t) \quad (3)$$

and, equivalently:

$$\begin{bmatrix} \mathbf{p}(t) \\ \frac{\mathbf{p}(t) - \mathbf{p}(t - \Delta t)}{\Delta t} \\ \frac{\mathbf{p}(t) - 2\mathbf{p}(t - \Delta t) + \mathbf{p}(t - 2\Delta t)}{\Delta t^2} \end{bmatrix} = \begin{bmatrix} \mathbf{I}_2 & \mathbf{O}_2 & \mathbf{O}_2 \\ \mathbf{O}_2 & \mathbf{I}_2 & \mathbf{O}_2 \\ \mathbf{O}_2 & \mathbf{O}_2 & \mathbf{I}_2 \end{bmatrix} \begin{bmatrix} \mathbf{p}(t) \\ \dot{\mathbf{p}}(t) \\ \ddot{\mathbf{p}}(t) \end{bmatrix} + \mathbf{v}(t)$$

where  $\mathbf{z}(t)$  represents the external observation (the detected position), and  $\mathbf{v}(t)$  represents the uncertainty in such an observation. Here we assume  $\mathbf{v}(t)$  is zero mean with a covariance matrix  $\mathbf{R}(t) = E[\mathbf{v}(t)\mathbf{v}^T(t)]$ . In correction stage, the new measurement (object's position computed by automatic detection and recognition system) is incorporated to update the state of Kalman filter model by the following process:

$$\mathbf{x}(t) = \mathbf{x}(t^-) + \mathbf{K}(t)(\mathbf{z}(t) - \mathbf{H}\mathbf{x}(t^-)) \quad (4)$$

The weighting factor  $\mathbf{K}(t)$  comes from summarizing the following three equations:

$$\mathbf{K}(t) = \mathbf{E}(t^-)\mathbf{H}^T(t)[\mathbf{H}(t)\mathbf{E}(t^-)\mathbf{H}^T(t) + \mathbf{R}(t)]^{-1} \quad (5)$$

$$\mathbf{E}(t^-) = \mathbf{A}\mathbf{E}(t - \Delta t)\mathbf{A}^T + \mathbf{Q}(t) \quad (6)$$

$$\mathbf{E}(t^+) = [\mathbf{I} - \mathbf{K}(t)\mathbf{H}(t)]\mathbf{E}(t^-) \quad (7)$$

where  $\mathbf{E}(t) = E[(\mathbf{x}(t) - \hat{\mathbf{x}}(t))(\mathbf{x}(t) - \hat{\mathbf{x}}(t))^T]$  is the error covariance matrix in the state estimation process and  $\hat{\mathbf{x}}(t)$  is the expected value for  $\mathbf{x}(t)$ .

For the  $\alpha\beta\gamma$  filter, the weighting matrix is given by:

$$K = \begin{bmatrix} \alpha \\ \beta/T \\ \gamma/T^2 \end{bmatrix} \quad (8)$$

where the optimum relationship between the parameters:  $\alpha$ ,  $\beta$  and  $\gamma$  that minimizes the mean-square error in the position, acceleration and velocity estimates, is given in [15] as follows:

$$\beta = 2(2 - \alpha) - 4\sqrt{1 - \alpha} \quad (9)$$

and

$$\gamma = \frac{\beta^2}{\alpha} \quad (10)$$

knowing that the parameter  $\alpha$  takes values between 0 and 1 and is adjusted experimentally.

#### IV. EXPERIMENTAL RESULTS

In our experiments, test sequences have been recorded with a video camcorder (Canon MVX30i) fixed onto the front windshield of a vehicle driving at usual speed. The resolution of each image is 720 x 576 pixels and the time between two ensuing frames is 0.2 sec. Currently, in our research we are particularly concerned with automatic inventory control of road signs and for this reason, sequences are run as batch processes. We have implemented the multi-road-sign tracking system using a 2.2 GHz Pentium 4-M. Fig. 6 shows the acting of the prediction for the trajectory of a traffic sign using two models: constant acceleration and constant velocity. Experimentally, the optimum value for  $\alpha$ ,  $\beta$  and  $\gamma$  are: 0.8, 0.61 and 0.47, respectively.

The sequences we have tested have been captured over a stretch of, approximately, 4 kilometers during both day and night time and one sub-sequence of them is shown in Fig.7, where we can observe as the road-sign is tracked even when

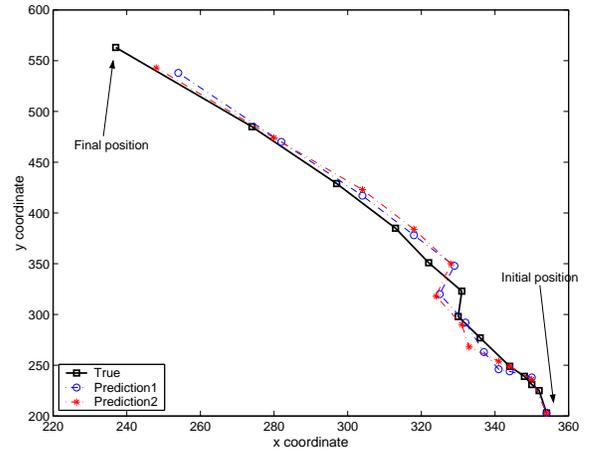


Fig. 6. Position prediction with a model of constant acceleration (Prediction 1) and with a model of constant velocity (Prediction 2).

an occlusion occurs due to the effect of the windscreen wiper. It is important to note that in each frame of the sequences the bounding-box of the detected sign is depicted and since, as we explained in section II-A, a sign can be processed as a sum of two contributions (the rim and the inner area), the same sign can be detected once or twice in each frame. Finally, the identified sign, which is tracked, is represented by a synthetic template in the upper-left corner of the image. In Table 1 are reported the number of images of both tested sequences, the number of traffic signs, the number of signs that are identified correctly after the tracking algorithm is applied and, finally, the number of false positives at the corresponding outputs of the detection system and the tracking sub-system, respectively. The number of false alarms at the detection's output represents all individual detections of objects whose geometric shapes are so similar to the habitual ones for traffic signs. This table shows how false alarms are practically eliminated by the tracking module because they do not present a temporal coherency in the sequence. Thus, the system gets an excellent detection rate in all the stretch. In Table 2 the results of individual detections are summarized, where we can observe how many times are detected the different signs of each sequence. It is important to point out that the number of times that a sign appears in a sequence is not constant and depends on several factors; mainly, the velocity of the vehicle.

#### V. CONCLUSION

In this paper, we describe the framework of a system for detecting and tracking road signs from a video sequence under various lighting conditions. The integration of the detection and tracking allows to dynamically predict the locations of road signs in the following frame even though in situations such as partial occlusion or no detection by possible failures of the detection and recognition system, attributed to incorrect segmentation, classification or recognition. Tracking algorithm improves the reliability of the whole system due to false alarms are difficulty confused with traffic signs in consecutive frames and in most cases are discarded. On the other hand, consecutive detections of the same sign are considered together as a

Sequence	Number of frames	Number of road-signs	Number of road-signs (Tracking)	False Alarms (Detection)	False Alarms (Tracking)
Seq. 1	914	27	27	18	1
Seq. 2	667	15	15	7	0

TABLE I  
QUANTITATIVE ANALYSIS OF THE DETECTION/TRACKING MODULES

Number of detections	Number of road-signs (Seq. 1)	Number of road-signs (Seq. 2)
2	2	1
3	3	2
4	9	6
5	8	4
6	3	2
7	2	0

TABLE II  
NUMBER OF INDIVIDUAL DETECTIONS OF TRAFFIC SIGNS

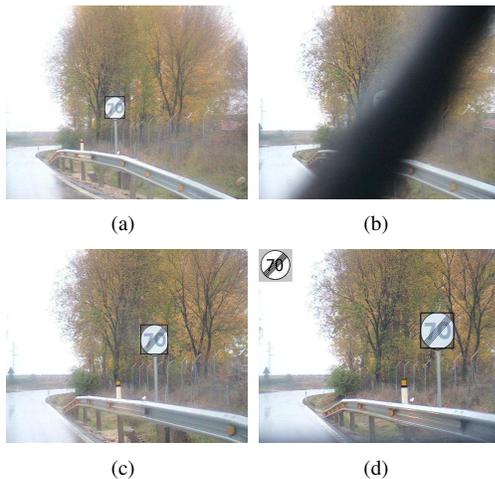


Fig. 7. Tracking results of a sequence.

single one. Anyway, a implementation of tracking submodule in detection step remains as a possible improvement.

Our future work will focus on estimating the physical sizes of road signs and extract some attributes relatives, such as deformation level, distance from the sign to the margin of the road, etc. On the other hand, in this work an optimization of computation time has not been developed and obviously, a real-time implementation is an improvement for future research.

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