Automatic Traffic Signs and Panels Inspection System Using Computer Vision

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***Abstract*—Computer vision techniques applied to systems used on road maintenance, which are related either to traffic signs or to the road itself, are playing a major role in many countries because of the higher investment on public works of this kind. These systems are able to collect a wide range of information automatically and quickly, with the aim of improving road safety. In this context, the correct visibility of traffic signs and panels is vital for the safety of drivers. This paper describes an approach to the VISUAL Inspection of Signs and panEls ("VISUALISE"), which is an automatic inspection system, mounted onboard a vehicle, which performs inspection tasks at conventional driving speeds. VISUALISE allows for an improvement in the awareness of the road signaling state, supporting planning and decision making on the administration's and infrastructure operators' side. A description of the main computer vision techniques and some experimental results obtained from thousands of kilometers are presented. Finally, the conclusions of the system are described.**

***Index Terms*—Computer vision, dynamic inspection, retroreflection, traffic signs detection, traffic signs recognition.**

I. Introduction

NOWADAYS, improving road safety is a key matter for road network management. Any company, organization, or institution responsible for the management and operation of any road network should be able to diagnose the problems related to the safety of drivers, set up a joint action plan, coordinate efforts among all the involved organizations, assign funds and resources, supervise the implementation of the action plan, and evaluate the effectiveness of the taken measurements. In this regard, there is a trend toward maintenance and optimization of the existing infrastructure instead of constructing a new infrastructure because supervising the state of conservation of the existing roads is more worthwhile than building new roads. Some works that show this tendency are [1]–[4].

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The most difficult decision that an engineer has to take is how and when a road should be repaired efficiently. Such an important decision cannot be taken without accurate information about the road's state. Among all the possible actions that can be taken, the evaluation and analysis of the traffic vertical signposting state are vital because of its interrelation with road users.

The European objectives for improving road safety [5] highlight the importance of having a good visibility of traffic signs and panels to avoid car accidents. In this regard, the European Commission states that making use of technical progress and collecting data of the roads' state are extremely important to detect potential dangerous situations.

Since it is vital that traffic signs are clearly visible at daytime and at nighttime from a suitable distance, the supervision of the quality of traffic vertical signposting is a key matter. Since traffic signs and panels are made of retroreflective materials that deteriorate with time, it is necessary to make a periodic test of vertical signposting.

To date, the inspection and measurement of the traffic vertical signposting retroreflection have been made using static pieces of equipment (retroreflectometers) that need to come into contact with the sign to be measured, thus leading to a clear danger, as operators have to stay beside the road, risking their own and other drivers' lives. In addition, it is necessary to close the road when panels above the road are measured. Typically, a few number of signs and panels are measured in a small stretch of the road, and the results are extrapolated to the whole road, but this technique is not efficient at all and can lead to wrong decisions.

Most of these problems could be solved if the inspection process were automated. However, to date, there are only a few systems that are able to develop inspection and inventory tasks automatically, and they have some limitations (see Section II). The state of the art is so reduced because of different factors. One of the main reasons is related to object detection in images, which is a difficult problem itself and is even more difficult at noncontrolled scenarios. Another reason is that traffic signs and panels have different colors and shapes. In addition, the necessity of using a mobile platform, typically a vehicle, adds complexity to the problem, particularly in scenarios where there is an unknown number of mobile objects.

VISUAL Inspection of Signs and panEls (VISUALISE) has been developed as a solution to the traffic vertical signposting inspection process. It is a tool to evaluate the traffic signs' state of conservation, according to the corresponding road signposting regulation.

This system is the result of the joint collaboration between the Robesafe Research Group at the University of Alcalá and a series of recognized and prestigious companies in road safety and inspection industries, such as Euroconsult,[1] 3M-Spain,[2] and Safecontrol.[3] VISUALISE is a patented dynamic inspection system for traffic signs (including those panels above the road), mounted onboard a vehicle, which is able to perform inspection tasks at conventional driving speed using computer vision techniques. This leads to a series of advantages versus the traditional means based on static measurements, as follows.

1) The presence of people and vehicles beside the roads, close to where the measurements are taken, is avoided.
2) The use of auxiliary bulky pieces of equipment to take measurements (particularly on panels above the road) is no longer necessary.
3) The efficiency of the inspection process is increased. Therefore, it is possible to analyze a larger number of signs in a shorter period of time.

All these pros lead to the most important one: a better awareness of the road network signposting state, which supports planning and decision making on the administration's and infrastructure operators' side and contributes to the improvement of road safety.

A review of the state of the art on traffic signs inspection is discussed in Section II. The VISUALISE operating principle is presented in Section III, whereas the inspection process overview is described in Section IV. Finally, the obtained experimental results and the drawn conclusions are shown in Sections IV and V, respectively.

II. State of the Art

Despite the fact that many works have been developed in the field of traffic sign detection and recognition [6]–[13], automatic traffic signs inspection using computer vision techniques has yet to be thoroughly studied. The main reason for the absence of works of this kind is that there is no global standardization on vertical signposting regulations, as each country has its own regulation. Another reason is that the parameter used to measure the quality of the traffic signs by the traffic regulatory agencies is the retroreflection, which cannot directly be measured by any vision-based system. Besides that, detection by using computer vision techniques in noncontrolled scenarios is an extremely complicated problem that has not been entirely solved.

Color segmentation is the most common method used for traffic sign detection and recognition. Some authors use standard color spaces such as RGB [6], [14]. Some other researchers prefer working with spaces that are more immune to lighting changes such as Hue, Saturation, Intensity [15], [16] or Lightness, U coordinate, V coordinate [17]. Because these methods cannot guarantee perfect color segmentation, other authors have developed more exhaustive color studies and classification techniques. A database for the color pixel classification was presented in [18], a fuzzy classifier in [19], a system based on deformable models in [7], a proposal based on support vector machines in [36], and another one based on textures in [14]. Color is an important piece of information to detect traffic signs, but the color variance can be very high due to different weather conditions, occlusions, and shadows. In conclusion, it is very difficult to obtain a global model for color segmentation. Some sophisticated approaches have been presented in the literature but, in most cases, with such a high computational cost that makes them impossible to use in real-time working conditions.

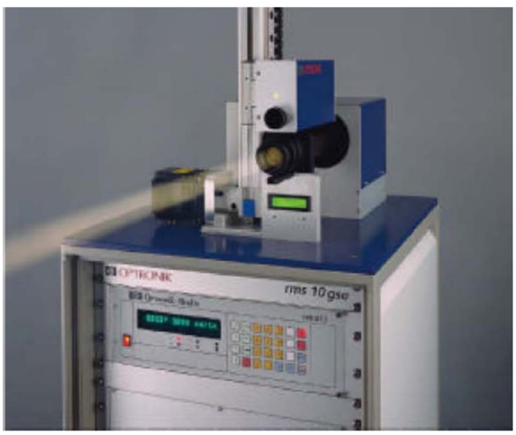
Other methods for traffic sign detection that are carrying out edge detection and shape recognition over grey-scale images have been developed. A robust-shaped detector like the Hough transform is typically used because it is very robust to changing illumination and occlusions. However, this transform is slow to compute over large images, and it has to work with a wide range of variation in the appearance of the traffic signs and panels over the images. Different algorithms have been proposed to reduce the computational time of the Hough transform; a multidimensional quadtree structure for accumulating is suggested in [26] (coarse-to-fine method), or in [27], a method based on the fact that a single parameter space point can be determined uniquely with a pair, triple, or generally n-tuple of points from the original picture (many-to-one mapping method). Barnes and Zelinsky [37] showed that by applying this method, the system is fast enough to work in real time but only with circular signs. Loy and Zelinsky [30] used a similar technique for triangular, square, and octagonal signs but not working in real time.

Most of the works in the literature apply detection and recognition techniques in a single-frame way. Owing to the complexity of the scenario, a sign classification based only on a frame is not reliable enough to discard all the false candidates. Information compiled through several frames can be used to corroborate or discard each candidate. Over the past few years, multiframe validation has been proposed by several authors. In [8], the detection system is sensitive to some particular image size, and a Kalman filter is used to track a sign through the frames until it is sufficiently large to be recognized as a specific standard sign. In [9], an automatic road-sign detection and recognition system that is based on a computational model of human visual recognition processing is presented. The main drawback of this strategy is that detection performance decreases with distance, then it is difficult to find robust trackers for longer distances to 50 m.

Traffic sign detection and recognition constitute the first steps of our inspection methodology. The main contributions of our proposal on these subjects are two. First, the application of Hough transform to restricted areas in the accumulation matrix, with no precision loss, allows us to detect triangular, square, diamond, octagonal, and circular shapes in a robust way and in real time. Second, we propose a novel multiframe validation method based on a backtracking strategy. Backtracking analyzes the image sequence in reverse direction with respect to the

[1] http://www.euroconsult.es
[2] http://www.3m.com/es
[3] http://www.safecontrol.com.ar/

(a)



(b)

Fig. 1. Manual inspection devices. (a) Example of a manual inspection device. (b) Example of a laboratory inspection device.

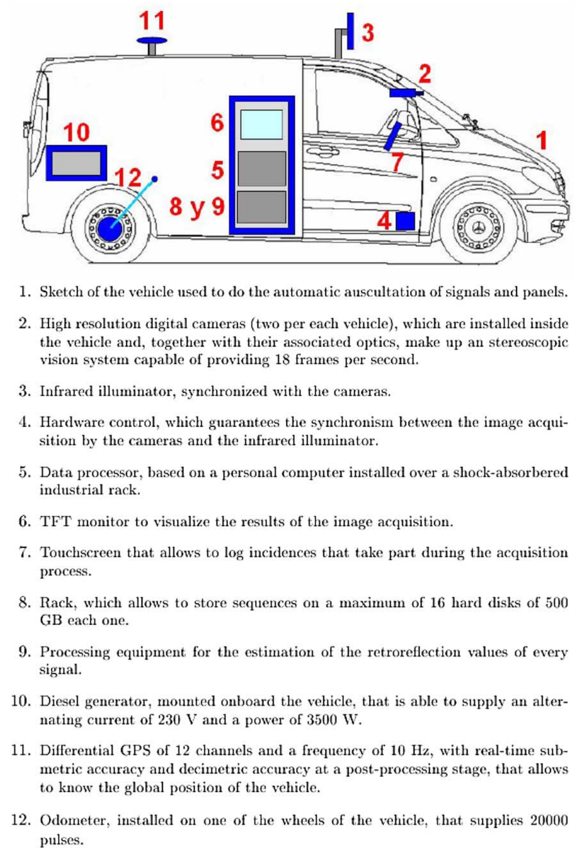


Fig. 2. VISUALISE system components.

recording one. This technique achieves a more robust tracking of every sign and panel up to longer distances than typical tracking methods. In addition, the relative distance between a sign and a vehicle is computed, combining stereo vision information with odometry information.

Focusing on the methods for vertical signposting inspection, the existing systems can be divided into two groups: manual and automatic inspection devices. Inside the first group, there are portable pieces of equipment, which are used to measure the retroreflection coefficient of a traffic sign or panel manually, and laboratory devices, which are used to carry out several experiments by modifying different parameters that affect the retroreflection measurement, such as the distance to the sign and the observation angle. Fig. 1(a) shows an example of a portable system. It usually consists of a reflectometer, a light source, a light detector, an amplifier, a display to read the measure, and a rechargeable battery. The geometry is typically fixed to an input angle of -4° and an observation angle of 0.2°. On the other hand, Fig. 1(b) shows a laboratory piece of equipment, i.e., the reflectometer RMS 10 GSE by Optronik. It consists of an illuminator and a reflected light receiver. The observation angle can be fixed from 0.2° to 20° [20].

The main drawback of the manual devices is that they need to come into contact with the element to be measured (or at a maximum distance of a few meters), which means having a huge number of disadvantages (as described in Section I). Automatic inspection devices solve these problems. To date, no automatic piece of equipment capable of taking retroreflection measurements has been developed, but there are some automatic systems whose goal is to analyze vertical signposting. The systems developed by AEPO [21] and GEOCISA [22] are intended to do an inventory of the traffic signs. The first system detects candidates to be traffic signs on the image by filtering colors and computing edges with a Canny detector and a Hough transform. The recognition is done by comparing each candidate to a set of pattern images. The system developed by GEOCISA [22] has a similar functionality as AEPO's system. Therefore, these systems are only used to do an inventory of the road network vertical signposting. On the other hand, the system SASV developed by the Technical Institute of Roadway Services and Transportation Systems [23] analyzes the visibility of traffic signs by evaluating the luminance data taken during the recording process. Unlike VISUALISE, the SASV system works with only one high-resolution camera, and therefore, it is not able to compute 3-D measurements. In addition, it does not take retroreflection measurements, and retroreflection is the parameter used to decide if a traffic sign is visible or not, because the regulation is based on this parameter due to the fact that manual devices give their measures in terms of retroreflection. The system described on this paper is able to give not only retroreflection values at a certain distance but retroreflection measurements at different distances as well, generating a curve that helps to take more reliable decisions than using just one single-point measurement. Then, the robustness of our proposal is very high because a novel

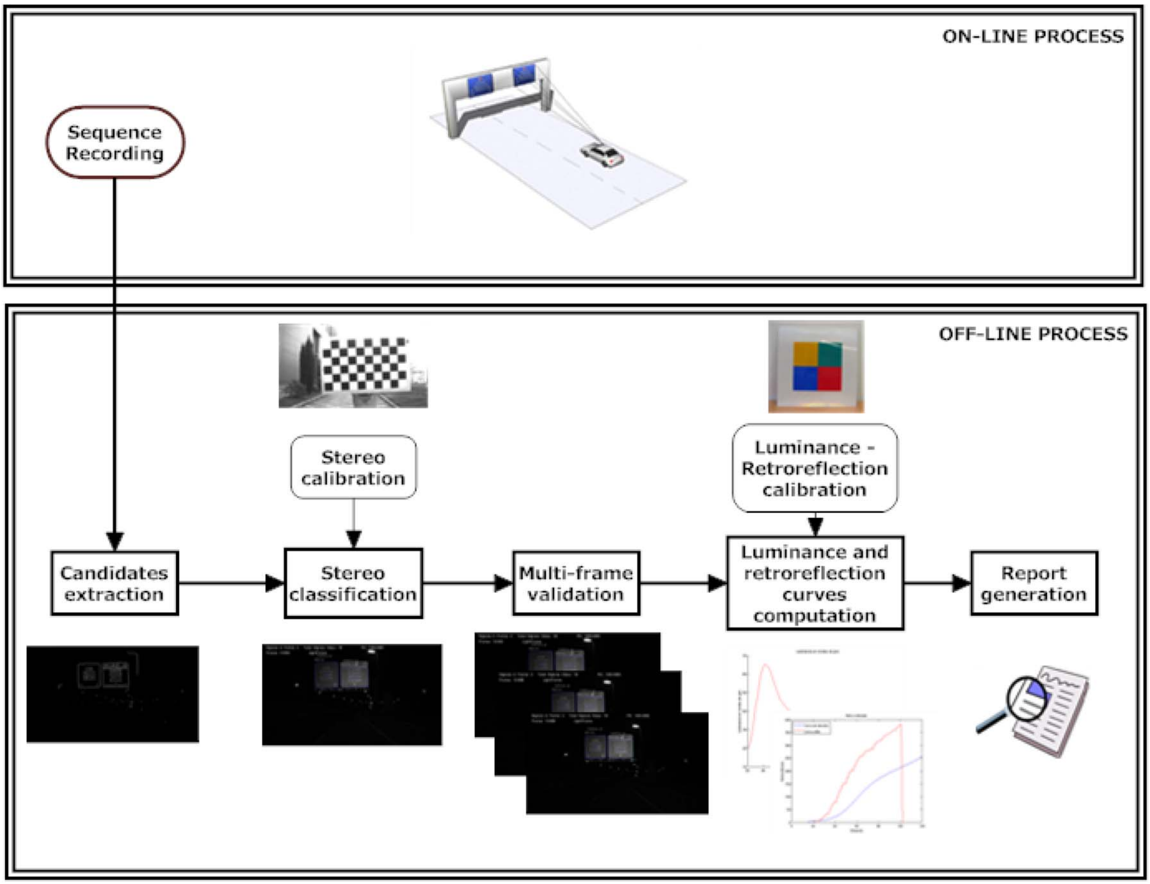


Fig. 3. Diagram of blocks of the inspection process.

approach to minimize the environmental lighting effect, using alternative illuminated and nonilluminated frames, has been carried out.

III. Operating Principle

The VISUALISE system is based on the light retroreflection principle. It uses an active infrared illuminator whose features are perfectly defined and known *a priori* as a pattern light source. Part of the infrared light that comes into contact with the signs and panels is reflected. The reflected light is captured by a stereoscopic system made up of two high-resolution cameras. As a consequence, the luminance level of the traffic signs, which is given in grey-level units by the two cameras, is directly proportional to the grade of luminance measured in candels per square meter units. The relation between luminance and retroreflection is defined by considering the distance and the angular orientation between the light source, the retroreflective material, and the measurement system (observation and input angles). This relation (luminance–retroreflection) is set through a prior calibration process.

Fig. 2 shows the location of the infrared illuminator, the cameras, and other hardware components onboard the vehicle.

The cameras are mounted on the windshield inside the vehicle looking forward at the road, with a base line of 35 cm, to guarantee the maximum precision when taking distance measurements, particularly at long distances. Both the position of the cameras and their angular aperture allow covering a minimum area of 10 m on each side of the vehicle for distances above 20 m. Therefore, the system is able to take measurements for every sign and panel located on the road: even those placed on both sides of the road. The cameras are calibrated with fixed values of gain and shutter, and the stereo system is previously calibrated.

The illumination system emits infrared light with a maximum power of 60 W. Such a low power guarantees that the infrared light does not affect the rest of the vehicles driving on the same road. Furthermore, the illuminator has an angular aperture of 30°, and therefore, it reaches a maximum illumination range of 170 m. The infrared illuminator is placed over the roof of the vehicle, equidistant to each camera, to guarantee that the light is homogeneously captured by each one.

The illumination system is controlled by an external synchronism signal. This signal allows synchronizing the illuminator with the cameras; therefore, the illumination of the scenario is taken out at alternative frames, which means that the light source is active while acquiring an image, and it is turned off in the following frame. Therefore, each sequence consists of pairs of illuminated stereoscopic images and pairs of nonilluminated stereoscopic images. The external synchronism signal is provided by a microcontroller. This signal is used to synchronize not only the infrared illumination system with the cameras but the acquisition times of both cameras as well to avoid temporal drifts between them.

IV. Inspection Process Overview

The inspection process can be divided into the following two steps with different tasks, as shown in Fig. 3.

1) Online process. A vehicle worked by two people (a driver and a supervisor) is used at this first stage of the process. The vehicle is equipped with all the necessary devices and software applications to carry out the acquisition and recording of the input stereoscopic sequences corresponding to actively illuminated roads by the onboard infrared illumination system.
2) Offline process. At this second stage, the previously recorded sequences are processed by using an image processing device based on a personal computer. As a result, a report, which contains the retroreflection and the contrast values of every sign and panel in the analyzed stretch of road, is generated.

A. Online Process

The goal at this stage is to carry out the acquisition of the stereoscopic sequences and the recording on a hard disk. Each one of these sequences consists of images of different road stretches illuminated by the onboard infrared illumination system. They are stored on removable hard disks, each one with a capacity of recording nearly 2.5 h, which is equivalent to inspecting up to 250 km.

The vehicle drives along the right lane with the aim of keeping the input angle of the light reflected by the signs and panels constant and not exceeding the maximum values of the materials used on the calibration process and guaranteeing that the signs and panels are correctly illuminated by the infrared illuminator.

B. Offline Process

The offline process takes the files generated in the previous process as input data. These files consist of sequences of stereoscopic images, Global Positioning System (GPS) coordinates, distance measurements provided by an odometer, and information supplied by the operator with a touch screen during the recording process. Then, the image processing algorithm is run to carry out the detection of signs and panels, the classification of each of them as a function of its luminance and shape, and the corresponding values of retroreflection and contrast (just in case this one is required). The main tasks of the algorithm are depicted in Fig. 3.

1) Candidate Extraction: The aim of the first step of the image processing algorithm is to detect the precise location of the signs and panels on the images. To achieve this, an analysis of the obtained shapes from an edge image is carried out. A Hough transform for straight lines is used to detect triangular signs, rectangular signs, and arrows, and a Hough transform for circles is applied to detect circular signs and the stop sign [24].

The algorithm used for edge detection is the Canny method. This method preserves contours, which is very important for detecting traffic signs using shape information because they are usually closed contours. The obtained contours applying the Canny method are codified using the chain code [25]. By making use of this codification, the area and perimeter are obtained, and it can also be determined whether a contour is closed or not. The contours are accepted if they are closed contours or almost closed contours. In addition, they must also fulfill an aspect ratio constraint typical of the traffic signs and panels geometry, according to the shapes shown in Fig. 7. The Hough transform is only applied to accept contours after being filtered with this kind of restriction, reducing the computational time. The strategy is to apply the Hough transform to every contour, one by one, unlike other authors [26], [27], [30], [37], who apply the

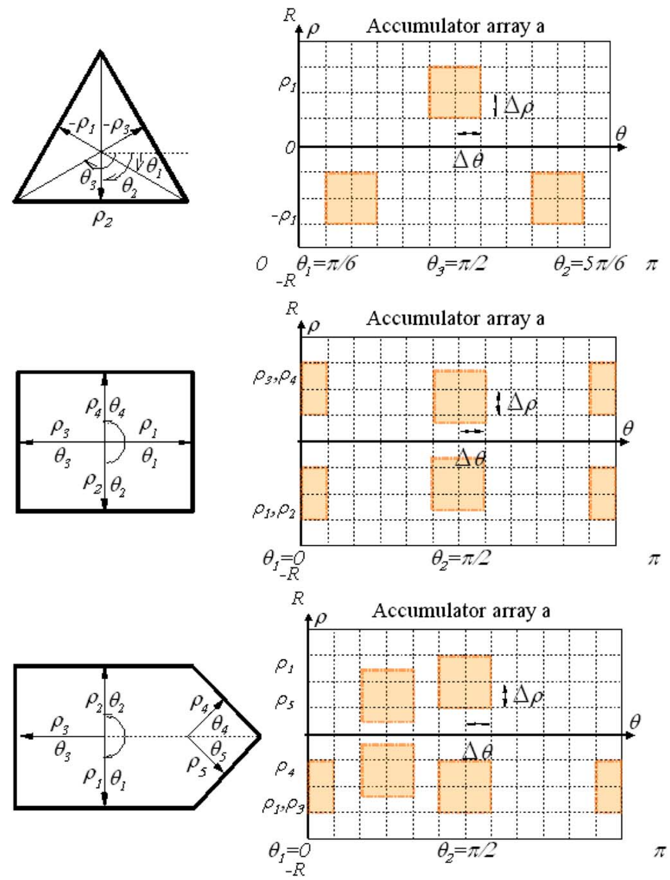


Fig. 4. Constrained Hough transform applied to detect triangular, rectangular, and arrow signs.

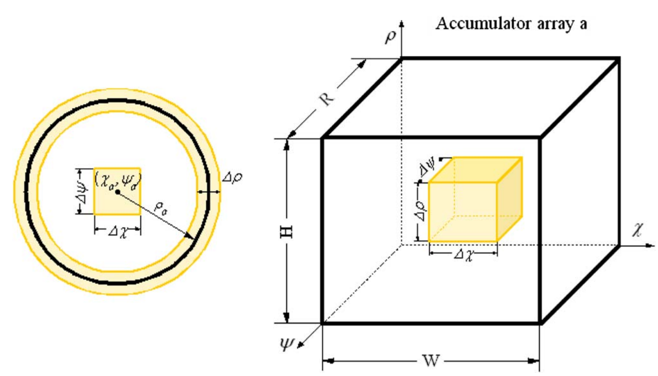
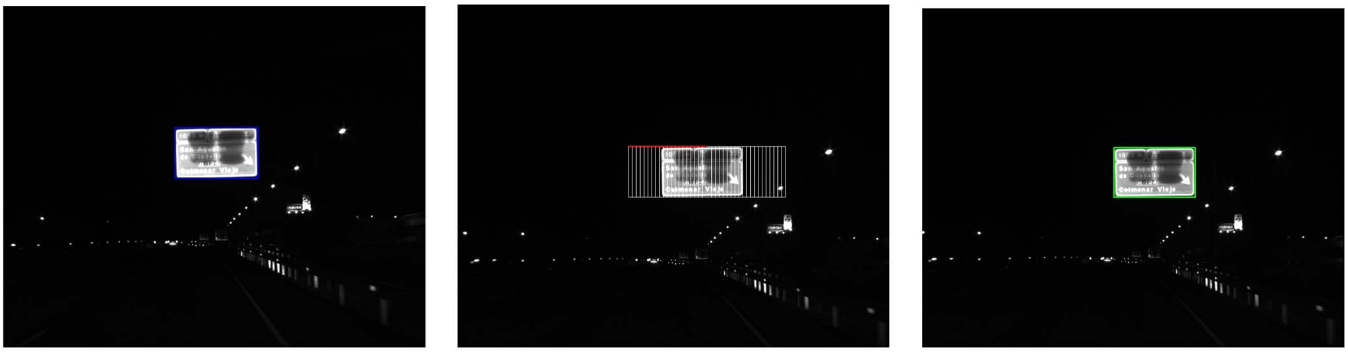


Fig. 5. Constrained Hough transform applied to detect circular signs.



(a) (b) (c)

Fig. 6. Stereo correlation. (a) Right image and bounding box of the detected panel. (b) Search space along the epipolar line corresponding to the upper left part of the bounding box on the left image. (c) Final match on the left image.

transform to the whole image. Thus, adaptive thresholds can be used depending on the size of each contour to detect the shapes of traffic signs. On the other hand, it is also possible to estimate the parameters that define these shapes to reduce the search space using a constrained accumulation matrix a. Hence, every straight-line-parameter estimation is calculated by means of

$$\rho = \frac{x_1 \cdot y_2 - x_2 \cdot y_1}{\sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}} \tag{1}$$

$$\theta = \arctan \frac{x_1 - x_2}{y_1 - y_2}. \tag{2}$$

where (x_1, y_1) and (x_2, y_2) are points belonging to the contour under study. These estimated parameters determine the search area within the matrix a, i.e., the shaded area in Fig. 4. A further explanation can be found in the authors' reference [24].

A similar strategy is followed for circular sign detection. Hough transform for circles is applied to detect circular signs and the stop sign as well. The circumference parameter estimation is calculated using the direction of the contour gradient under study, as in [29] and [30]. The search range into the accumulator matrix a is constrained; the circumference parameters are only searched inside shading areas, as can be seen in Fig. 5. The main contribution of this step is the application of the Hough transform to restricted areas in the accumulation matrix, with no precision loss. With this strategy, we are able to detect triangular, square, diamond, octagonal, and circular shapes in a robust way and in real time.

2) Stereo Classification: An accurate estimation of the relative position between the vehicle and the signs or panels has an important impact on further stages, such as tracking, geometrical discarding, and luminance–retroreflection curve computation. To minimize the distance estimation error, the relative distance is computed by combining the stereo vision sensor with the odometer.

Stereo parameters (camera focal length, baseline, and image sizes) have been defined, giving priority to the distance estimation error. The content of the detected bounding boxes is matched along the epipolar line on the other stereo image, as in [31], reducing the disparity search space according to the minimum and maximum ranges. This process is illustrated in Fig. 6(a)–(c). The correlation values are obtained, and the values near the optimum are approximated by a second-degree polynomial to compute the 3-D position with subpixel accuracy [32].

The use of stereo vision involves two main drawbacks. First, the computational costs are too high. Second, stereo errors are proportional to distance [33]. As a consequence, depth measurements corresponding to signs or panels at long distances are not reliable enough. To minimize these aspects, we propose a novel strategy based on a backtracking approach in which the analysis of the images is carried out in reverse order. Accordingly, the initial appearance of the sign takes place at the minimum relative distance (once the whole sign is visible in both cameras), i.e., with the minimum possible stereo error. Thus, the relative distance between the vehicle and the sign is initialized with the best stereo measurement $d0 = z0$. The remainder measurements are updated by adding up the vehicle displacement dvt, which is provided by the odometer, i.e., $dt = dt - 1 + dvt$. This strategy is followed for two main reasons. First, the computational cost is reduced since stereo measurements are only obtained during the first iterations. Second, although the odometry error is cumulative (1 m per each 100 m), considering the detection range (100 m for signs and 170 m for panels), this error will be always much lower than the error provided by the stereo sensor at long distances.

The vehicle global position is accurately obtained from the differential GPS. However, the GPS sample frequency is 1 Hz, which implies that the system obtains one GPS measurement per each 20–30 m approximately. As the storage process is carried out at 18 Hz, some kind of interpolation is needed. We apply linear interpolation between two consecutive GPS measurements using the values provided by the odometer, whose sample frequency is ten times higher (100 Hz).

Finally, a global reference for each one of the detected signs and panels is obtained by combining the global position of the vehicle and the relative position between the vehicle and the sign or panel. The global position of the signs and panels is extremely useful from the point of view of both inspection and inventory tasks.

3) Multiframe Validation: To improve the detection figures in single frames, we propose a multiframe validation strategy.

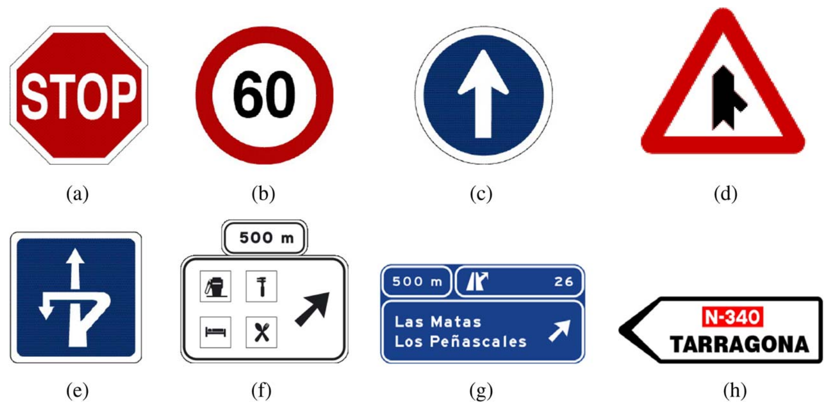


Fig. 7. Types of signs and panels. (a) Stop sign. (b) Circular sign (white background). (c) Circular sign (blue background). (d) Triangular sign. (e) Rectangular sign. (f) Panel (white background). (g) Panel (blue background). (h) Arrow panel.

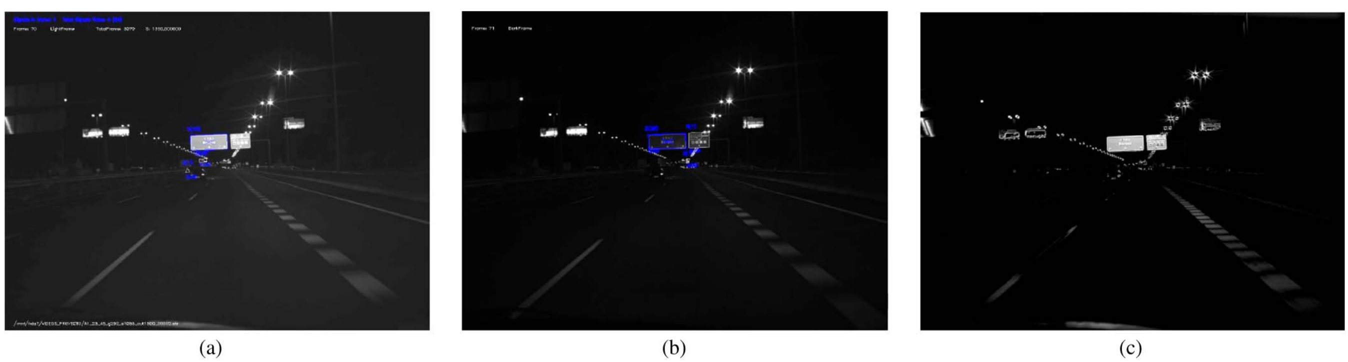


Fig. 8. Frame subtraction. (a) Illuminated frame. (b) Nonilluminated frame. (c) Subtraction frame.

The multiframe validation consists of a dynamic tracking of every candidate, a search through region-matching techniques, and a verification of the coherence in terms of the 3-D position. To do this, it is necessary to match the extracted candidates with the signs detected in the previous frames. To decide if a candidate in the current frame represents the same sign than a candidate in the previous frame, a score table that contains, for each pair of candidates, the probability of representing the same sign is made. Each value of the score table is computed by taking into account the position of each candidate in the image. However, it is crucial to set a restriction in the movement of the candidates between two consecutive frames to limit the number of possible associations. To estimate and update the position and size of every candidate, Kalman filtering is used.

The state vector consists of six parameters, as can be seen in (3): the position (x, y) of the sign center in the image plane and the addition of the sign height and width r, together with the velocity of variation for each one, i.e.,

$$X = (x, y, r, v_x, v_y, v_r). \tag{3}$$

When a sign cannot be associated with any candidate, region matching is done. It consists of a displacement of a pattern image, the one that is wanted to be found, over an image of larger size. For each position of the pattern over the image, the correlation between both images is computed, thus obtaining a normalized correlation coefficient map. Then, the position that corresponds to the higher correlation value is chosen.

Finally, it is necessary to detect the signs and panels in the nonilluminated frame to do the subtraction of the luminance between two consecutive illuminated and nonilluminated frames. A sign interpolation between two consecutive illuminated frames, which are precedent and subsequent to the nonilluminated one, is carried out. If the displacement of the sign or panel between two consecutive illuminated frames is d and the sign growing factor is f, then the displacement at the nonilluminated frame is $d/2$, and the growing factor is $\sqrt{f}$. With this method, we obtain higher detection percentages than using single-frame detection.

4) Sign Classification: Each detected sign and panel is later analyzed as a function of its luminance and shape to classify it into one of the following categories, which are depicted in Fig. 7:

1) stop sign;
2) circular sign with white background;
3) circular sign with blue background;
4) triangular sign;
5) rectangular sign with blue background;
6) panel with white background;
7) panel with blue background;
8) arrow panel.

These eight classes represent the different shapes of the traffic signs and panels established in the Spanish regulation described in [38].

5) Luminance and Retroreflection Curves Computation: For each type of sign and panel, a segmentation process is carried out to separate their basic elements (border, text pictogram, background). To minimize the effect of environmental lighting, a subtraction of the luminance values measured by the two cameras in two consecutive frames is carried out. Therefore, practically, the whole luminance of the signs and panels comes from the illumination emitted by the infrared illuminator. This novel approach guarantees maximum homogeneity on the measurement conditions. The mean value of the luminance in grey scale is calculated for each part of the sign. This is done for every single image where the sign or panel is detected, and therefore, it is possible to obtain a luminance curve for each basic element as a function of the measured distance.

The implemented segmentation method must be robust enough against some typical problems in computer vision, such as the following:

1) occlusions and shadows due to other objects;
2) noncontrolled lighting conditions;
3) image saturation;
4) signs insufficiently illuminated when placed out of the angular aperture of the illuminator;
5) a wide range of variation in the appearance of the traffic signs and panels in the image.

To manage these problems, a couple of techniques have been implemented. First of all, frame subtraction has been used to minimize the effect of noncontrolled illumination, such as road illumination and car lights, so that the luminance measurement only depends on the infrared illumination. Fig. 8 shows the decrease of external lighting influence on the subtracted frame.

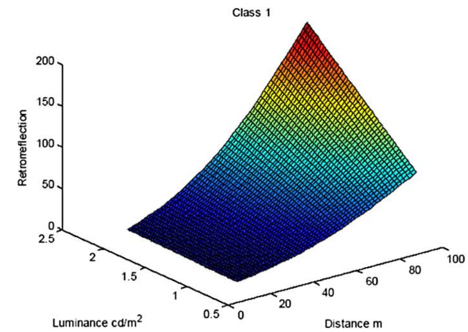
Second, an illumination correction method is applied to minimize the nonuniform illumination that arises in traffic signs and panels due to the aperture angle of the illuminator. An estimation of the sign background by smoothing the grey levels of the sign is carried out.

The segmentation method implemented is based on Otsu's algorithm [35], which is an automatic adaptive technique that computes the optimum thresholds by maximizing the interclass variances. This method is applied over the subtracted frame after applying the aforementioned illumination correction method. Then, each sign or panel is segmented in their basic elements.

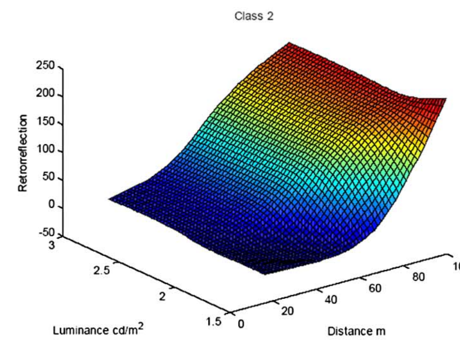
Later, to obtain the luminance curves for each traffic sign and panel, the backtracking approach is used, which makes it possible to get measurements of luminance of the background elements up to 100 m for signs and up to 170 m for panels.

These curves are turned into retroreflection curves as a function of the distance. To achieve this, different conversion surfaces are used. These surfaces use the grey-scale luminance and the distance as inputs, and they provide the retroreflection value estimated as output.

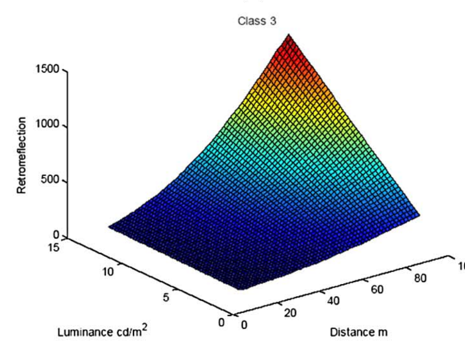
According to the Spanish regulation [38], three different curves are used, i.e., one for each retroreflective material with which the signs and panels can be made: levels 3, 2, and 1. The assigned curve to each sign or panel will be the one for which a better adjustment for each hypothesis is obtained. These conversion surfaces are computed through a prior calibration process. Fig. 9 shows the three different conversion surfaces and the appearance of the level-3 pattern sign used in the calibration process. This is a methodology patented by the authors.



(a)



(b)



(c)

(d)

Fig. 9. Conversion surfaces obtained during the calibration process. (a) Class 1. (b) Class 2. (c) Class 3. (d) Class 3 pattern sign.

Three pattern signs with known retroreflection values as a function of the distance, which are made of level-1, -2, and -3

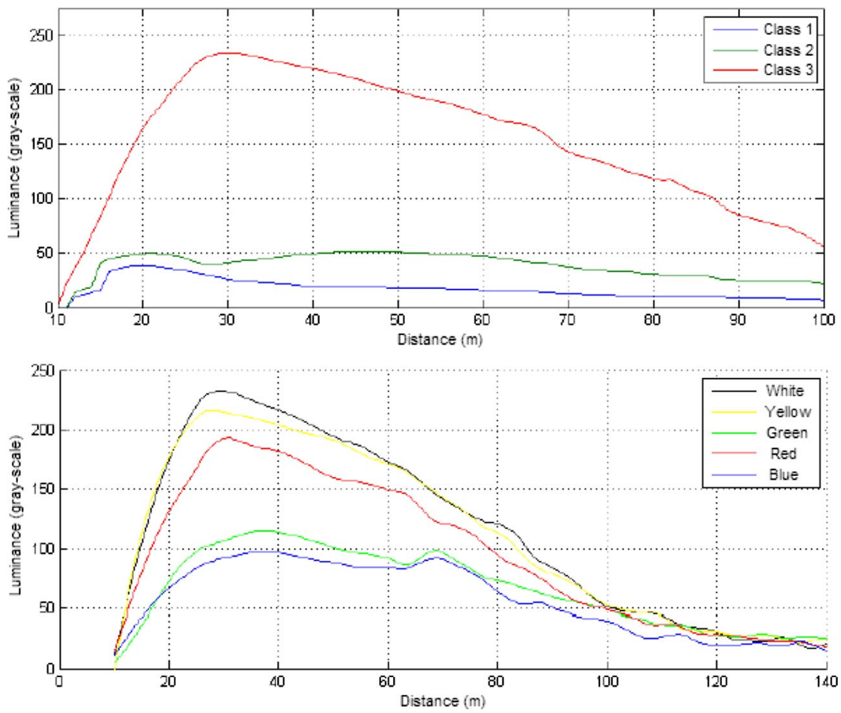


Fig. 10. Luminance curves of the white color for each pattern sign (upper) and luminance curves of each color for the level-3 pattern sign (lower).

materials, are used in the calibration process. A video sequence is acquired for each pattern sign by using the vehicle to be calibrated and all its onboard equipment. Fig. 10 shows the results obtained on a real calibration experiment. On the upper part of the figure, the grey-scale luminance curves of the white color for each material are depicted, whereas the lower part of the figure displays grey-scale luminance curves for each color for the level-3 pattern sign.

In the calibration process, different pattern signs are placed at the typical positions of traffic signs in a test road. The vehicle drives along the right lane at a lateral distance of 5 m on the sign. The vehicle starts driving 200 m away from the sign, and it moves toward the sign until it disappears from the cameras' view. The recorded sequences are then processed for obtaining the luminance curves as a function of the distance for each one of the three pattern signs.

The three conversion surfaces are obtained from the three luminance curves and the retroreflection values measured manually at several distances for each pattern sign. Fuzzy nonlinear regression techniques are carried out to obtain the surfaces. Therefore, three retroreflection curves as a function of the distance, i.e., one for each material, are obtained from the luminance curves. Fig. 11 shows the retroreflection curves obtained after the calibration process for each material.

The retroreflection value of the white part of the sign, which is measured at a distance of 100 m, corresponds to the standard measurement for an input angle of 5° and an observation angle of 0.33°, because of the geometry given by the location of the cameras and the infrared illuminator. Retroreflection at the 100-m measurement is used for the current manual inspection systems to establish if a sign fulfils the regulation relative to the minimum retroreflection value accepted for a traffic sign.

As it was said previously, the retroreflection measurements of the parts that do not belong to the sign background, such as the border or the text pictogram, can be used to calculate the contrast ratio between the primary and secondary colors of the sign. This contrast ratio can be seen as an indicator of the legibility of the traffic sign.

Besides that, the retroreflection curve can be compared with the retroreflection ground truth established on the regulation for each material. This comparison allows determining if the sign fulfils the regulation, which depends on the road where the sign is located.

6) Report Generation: Finally, the system generates a report that has the following information for each sign and panel:

1) retroreflection curve as a function of the distance;
2) retroreflection value at 100 m;
3) contrast ratio at 100 m;
4) type of road;
5) milestone;
6) GPS coordinates;
7) height above the ground;
8) lateral distance from the center of the lane where the vehicle is moving;
9) road;
10) carriageway;
11) lane;
12) material;
13) type of sign or panel (circular, triangular, rectangular, panel, arrow);
14) fulfillment of the regulation relative to the retroreflection value depending on the material of the sign.

All of the information is managed by a graphical user interface that allows the contents of the report generated for each stretch of the analyzed road to be gone through.

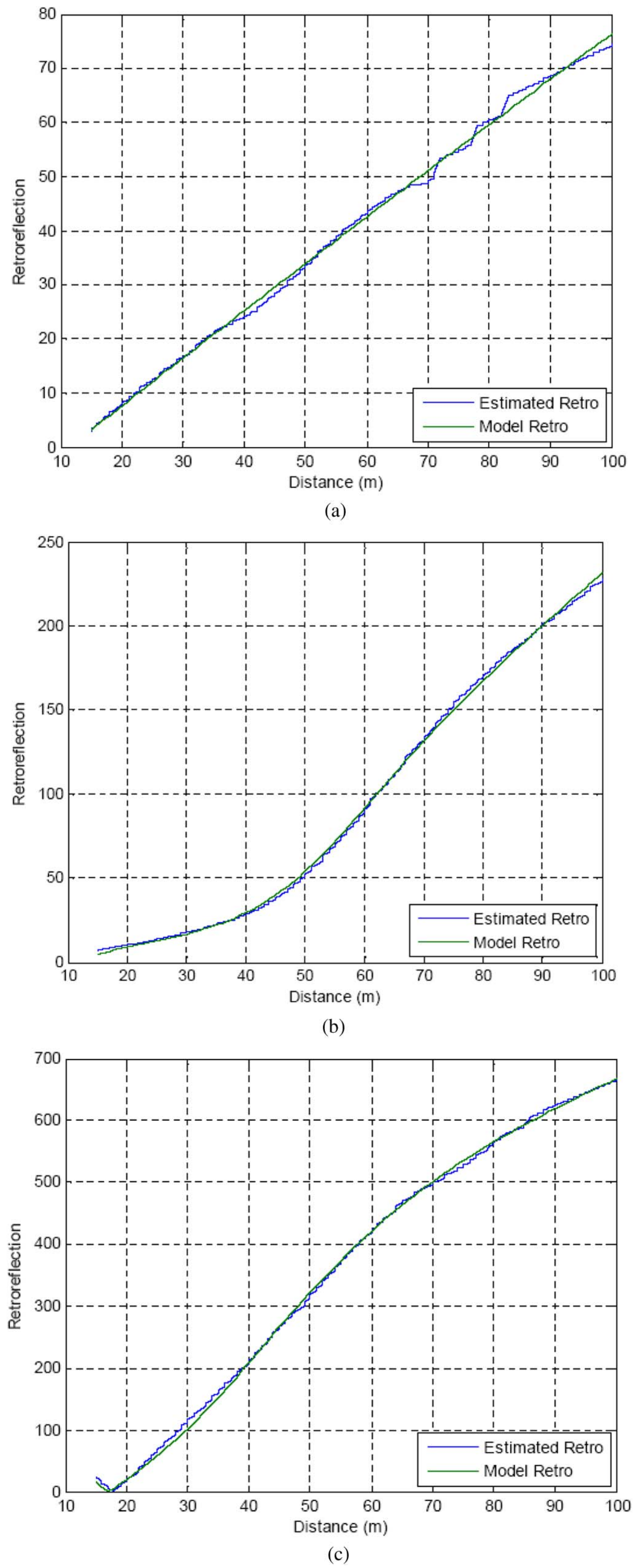


Fig. 11. Ideal and real retroreflection curves of each pattern sign. (a) Class 1. (b) Class 2. (c) Class 3.

V. Experimental Results

To check the reliability of VISUALISE, several experiments have been carried out. Two inspection vehicles were assembled,

Fig. 12. Inspected roads.

and more than 5000 km of the Spanish road network was inspected with these vehicles for checking the reliability of the recording system and the performance of the processing software in different road scenarios. These roads can be seen in Fig. 12. The number of kilometers for each road was 500 km for A-1, 680 km for A-2, 700 km for A-3, 500 km for A-31, 1100 km for A-4, 800 km for A-5, and 1000 km for A-6. All the measurements were taken during the summer because it is the time of year when the air humidity is at a minimum, and at nighttime, from 12 A.M. to 5 A.M., because the system has been designed to work at nighttime when there is lower traffic density. An approximate total of 50 000 signs and panels were measured. On the other hand, more than 500 signs and panels from different roads were randomly chosen as ground truth, which means that they were also measured manually, and these values were compared with the results obtained with VISUALISE.

Manual measurements are taken using calibrated retroreflectivity equipment that use a narrow light beam emitter. This implies that manual measurements need to be taken, in particular, selected points of the sign or panel under inspection. Normally, several manual measurements are performed (up to five) on each color band of each sign so that the assigned retroreflectivity value for such band of such sign is the average value of all manual measurements. On the other hand, VISUALISE automatic measurements are carried out based on the luminance value of all visible points in the sign. Considering the fact that real traffic signs and panels may show different retroreflectivity behaviors in different parts of their body as they may deteriorate heterogeneously, it is reasonable to expect that some minor discrepancies between manual measurements (based on a finite set of points) and VISUALISE measurements (based on the whole sign surface) might arise.

Analyzing the results, the system is able to detect up to 99% of the signs and panels present on the road. As there are typically occlusions owing to vegetation or other vehicles, not all of the detected signs are valid to get a reliable retroreflection measurement. Therefore, it has been decided to get a minimum of ten samples at different distances from a certain sign or panel to get a reliable retroreflection curve of it. As a consequence, only 97% of the total of signs present on the road are valid to

TABLE I
PERFORMANCE OF THE VISUALISE SYSTEM

	Percentage over the total of signs present on the road
Percentage of detection	99.52%
Percentage of measured signs	97.62%
Percentage of reliability	91.66%

TABLE II
DETECTION RATIOS FOR HOUGH TRANSFORM VERSUS GROUND TRUTH

Signs	Detected signs	Valid signs (*)
Stop	99.92%	98.92%
Circular	99.92%	98.92%
Rectangular	99.46%	96.79%
Triangular	99.94%	99.94%
Arrow	93.75%	93.75%
Panels	99.96%	99.96%
TOTAL	99.52%	98.10%

(*) Valid signs are those for that we have at least 10 correct detections.

get a retroreflection curve. After comparing the measurements obtained with the dynamic system to the manual measurements, the main conclusion that can be pointed out is that the reliability of the VISUALISE system is above 91% in terms of signs and panels correctly classified into accepted (signs that fulfill the minimum retroreflection values stated in the regulation) or rejected (signs whose material or retroreflection values are below the minimum required by law). Table I summarizes these statistics.

Focusing the analysis on the detection and classification performance, Table II shows the detection ratios of the Hough transform for the different types of signs and panels regarding its shape. As can be seen, six different types are defined instead of the eight types defined in the classification task, because circular signs with blue and white backgrounds have been considered in the same category according to its shape. The same consideration has been taken into account for the panels. A differentiation between detected and valid signs is carried out. Valid signs are those for which there are ten correct detections at least. As a consequence, a reliable curve of retroreflection can be calculated for it if a valid luminance measurement is obtained for each detection. The total detected signs ratio is 99.52%, and the total valid signs ratio is 98.10%. These ratios are very high considering the large number of signs and panels tested. The highest ratio is obtained for the panels, followed by triangular, circular, stop, and rectangular signs. The worst detection ratio is achieved for the arrow type. The more complex the shape of the sign is and the smaller its size is, the lower the detection ratio is. Stop and circular signs have the same detection numbers because stop signs are detected using the circular Hough transform, as it is also done for circular signs. The circular Hough transform is applied to detect stop signs because they have a circular appearance in the images from the distance where our system begins to measure.

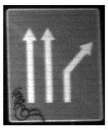
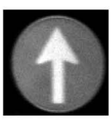
Tables III and IV show the comparison between the manual measurement and the dynamic measurement of different signs with examples of hits (see Table III) and misses (see Table IV). At this point, it is crucial to notice that each type of material has a minimum retroreflection value at 100 m, as required by law. These minimum values are, according to the Spanish regulation, 49 cd/m^{2}lx for a level-1 sign, 126 cd/m^{2}lx for a level-2 sign, and 212.5 cd/m^{2}lx for a level-3 sign. This is the reason why some signs are rejected, although the material's class is correct.

As stated previously, not all of the detected signs are valid to get a reliable retroreflection measurement, and a minimum of ten samples is required. Even so, there are signs whose measurements can be erroneous for of different reasons. Among the possible causes are graffitis, occlusions because of vegetation or other vehicles, shadows due to other signs or panels, and inclined signs. This leads to misclassification in terms of the material, because a sign or panel can be classified into a lower level if the measurements are erroneous. This mainly affects those small signs located on the sides of the roads. Table IV shows some examples. The first and third signs have not been correctly tracked. The second sign does not have enough samples to get a reliable measurement. The fourth sign is erroneously rejected, although manual retroreflection refers to the white part of the panel that is in the best condition, whereas the rest of the panel is much more deteriorated. As the VISUALISE measurement refers to the whole panel, it can be said that the VISUALISE measurement is more reliable than the manual measurement in this case. The fifth sign is erroneously rejected because it has been wrongly segmented, as it has been grouped with another sign that is ahead of it. The last sign has been wrongly measured as it is inclined with respect to the road. As can be seen, misclassifications are due to discrepancies between manual and VISUALISE methods. In some cases, we consider that the VISUALISE method is more reliable than the manual method, despite the fact that some results were initially classified as errors. However, the ground truth methodology is not foolproof.

VI. CONCLUSION AND FUTURE WORK

Unlike manual devices, VISUALISE is able to get several luminance measurements of a sign in the range from 15 to more than 100 m. It is also capable of classifying a sign or panel into a certain class of material by comparing the luminance measurements with a model obtained through a prior calibration process. In addition, unlike other automatic inspection systems, VISUALISE calculates retroreflection values from luminance measurements and checks if the sign fulfils the minimum values at 100 m, as required by law.

TABLE III
COMPARISON BETWEEN MANUAL MEASURES AND THE VISUALISE SYSTEM. HITS

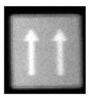
Sign	Road	Mimimum level required by law	Level assigned by VISUALISE	Manual retroreflection measure at 100 m. (cd/m^2lx)	Retroreflection measure by VISUALISE at 100 m. (cd/m^2lx)	Decision
	A1	2	2	191.22	218.96	Accepted
	A1	2	1	70.77	96.07	Rejected because of a lower material
	A1	2	2	206.55	225.36	Accepted
	A1	2	2	75.88	74.66	Rejected because of a lower retroreflection
	A1	2	3	453.88	513.08	Accepted
	A1	3	3	571.33	492.67	Accepted
	A1	3	3	55.00	49.84	Rejected because of a lower retroreflection
	A2	2	1	90.06	95.98	Rejected because of a lower material
	A2	3	3	447.00	503.43	Accepted
	A2	2	1	19.90	20.34	Rejected because of a lower material

The obtained results show that the retroreflection values given by VISUALISE are really accurate, as they have a small error compared with the ground truth taken manually. In addition, it makes an inventory of the signs and panels.

VISUALISE has been designed to have a processing capacity of 1 : 1, which means that only 1 h of processing is necessary for each hour of recording. As a consequence, this system is a good solution to the inspection problem, as it is able to analyze the majority of the signs and panels located on a road in a short period of time.

Focusing on the traffic sign detection and recognition algorithms, our main contributions are the following: the application of the Hough transform to restricted areas in the accumulation matrix, with no precision loss, obtaining robust shape detectors in real time; the multiframe validation method based on a backtracking strategy, which achieves a more robust tracking of

TABLE IV
COMPARISON BETWEEN MANUAL MEASURES AND THE VISUALISE SYSTEM. MISSES

Sign	Road	Mimimum level required by law	Level assigned by VISUALISE	Manual retroreflection measure at 100 m. (cd/m^2lx)	Retroreflection measure by VISUALISE at 100 m. (cd/m^2lx)	Decision
	A2	2	2	94.30	196.18	Erroneously accepted due to tracking error
	A2	2	2	159.45	97.36	Erroneously rejected because of few samples with low reliability
	A2	2	2	169.15	85.95	Erroneously rejected because of tracking error
	A1	3	2	635.66	220.53	Erroneously rejected because retroreflection is obtained in the whole panel and not only in the white part
	A1	2	1	162.55	86.58	Erroneously rejected due to the segmentation process
	A1	2	2	158.11	99.39	Erroneously rejected because of a wrong position of the sing

every sign and panel up to longer distances than typical tracking methods; and the robust calculation of the relative distance among signs and the vehicle using stereo vision and odometry data fusion.

In conclusion, VISUALISE supposes an advance with regard to road signposting evaluation. It represents a boost for the improvement of the state of maintenance of the road's signposting. Actually, the better awareness of road's signposting state will allow for the planning of more efficient road maintenance and, consequently, optimization of the budget allocated for this purpose. This will definitely help to improve road safety.

As for future work, we are planning to increase the system ratios through the experience to be obtained from the kilometers that are planned to be inspected in Spain (more than 30 000) and to adapt the system to other countries' signposting regulations.

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