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Robust Traffic Signs Detection by means of Vision and V2I Communications

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***Abstract*— This paper presents a complete traffic sign recognition system, including the steps of detection, recognition and tracking. The Hough transform is used as detection method from the information extracted in contour images, while the proposed recognition system is based on Support Vector Machines (SVM), and is able to recognize up to one hundred of the main road signs. Besides a novel solution to the problem of discarding detected signs that do not pertain to the host road is proposed, for that purpose vehicle-to-infrastructure (V2I) communication and stereo information is used. This paper presents plenty of tests in real driving conditions, both day and night, in which a high success rate and low number of false negatives and true positives were obtained, and an average runtime of 35 ms, allowing real-time performance.**

I. INTRODUCTION

The importance of safety for drivers, occupants and pedestrians has experimented an increasing interest in the last times, and traffic sign recognition (TSR) systems, within the Advanced Driving Assistance Systems (ADAS), play an important role, allowing alert drivers to potential dangerous situations, for example when a driver may be speeding. But not only it is useful as a driving-assistance system, TSR also has other possible applications, such as inventory system of traffic signs [1], or building and maintaining maps of signs, furthermore it can be used as automatic inspection of signs. For example, VISUALISE system [2] provides automatic retro-reflection measurement of traffic signs and panels, allowing better maintained roads resulting in better and safer signposting.

In this paper we present a complete traffic signs recognition system able to detect both circular and triangular signs and recognize up to one hundred of the main road signs. In outdoor detection, lighting conditions cannot be controlled, for this reason analysis of the edges from grey-scale images have been used instead of colour-information that presents, in general, worst results under adverse lighting conditions, such as at night. The classification stage is carry out by two support vector machines (SVM) with Gaussian kernels. In detection stage circular and triangular road signs can be distinguished, so a SVM for circular signs and another SVM for triangular signs are applied. Finally, tracking of traffic signs is implemented using Kalman filtering techniques, for this purpose, a dynamic state model is defined, where measurements are obtained by means a stereo pair of calibrated cameras.

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One of the challenge still open in traffic sign recognition is to discard detected signs that do not pertain to the host road. The position of each detected traffic sign is obtained from stereo pair of cameras and those whose position are far from the vehicle lane will be discarded. However, there are some scenarios where the 3D relative position is not enough for discarding signs that do not apply to the host road, in those cases information from vehicle-to-infrastructure (V2I) communication system is proposed as solution, so V2I communication system using, wireless technology, works as support of the traffic sign recognition system.

II. RELATED WORK

An automatic traffic sign recognition system can detect signs by their colour and shape, just as a driver. However, in the literature we can find two main approaches to solve the problem of traffic sign recognition; segmentation, using colour-information, or analysis of the edges obtained from grey-scale images. In working with colour-information relations between red-green-blue (RGB) components are used, [3], [4], but RGB colour-space is highly dependent on the light, so other researchers work with hue-saturation-intensity (HSI), [5], [1], [6], this colour-space is more immune to lighting changes, thus in [5] two look-up tables (LUTs) for hue and saturation components are used to enhancement red and blue colours, while in [1] a threshold over hue and saturation components is applied to find regions with high probability of having a traffic sign. However, the captured image is not completely invariant against changes in the chromaticity of the received light. The hue component changes with shades, climatic conditions or aging. Some works improving the colour segmentation are carried out. For example in [7] a human vision colour appearance model CIECAM97 is applied to extract colour information and to segment and classify traffic signs.

Among the works in which edge-analysis starts from the grey-scale image, [8] must be highlighted, where Gavrila uses a template-based correlation method to identify potential traffic signs in images; this involves the so-called distance transforms (DT), starting form an edge-image, a matching with the template of those signs searched is carried out. These templates are organized hierarchically in order to reduce the number of operations, however, this method has a high computational cost for a real-time system. Another work to be explained a bit more deeply is the one developed by [9],

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related to our work, as a variation of the Hough-transform (HT) is used. The method used by Barnes is based on [10], a fast method to detect points of interest using a system with radial symmetry. It uses the information of the magnitude and phase of the gradient of a grey-scale edge-image for different radii. Although the method is able to detect only circular signs it has been extended to detect triangular, square and octagonal signs in [11]. A self-organizing map (SOM) has been used in [12] to extract contours in order to recognize shapes of traffic signs. Histograms of oriented gradient (HOG) have been used in [13] for pedestrian and road sign detection, which is suitable within boosting frameworks. In recent times, new approaches in object detection have been applied. In [14] a set of colour-sensitive Haar wavelet features has been obtained from AdaBoost training and temporal information propagation, while in [15] a novel binary classifier through an evolutionary version of AdaBoost has been proposed.

The following stage is the classification one; the resultant image from the first stage is analysed in this one by a classifier that determines whether the previously detected candidate regions are actual traffic signs or not. Neural networks, in their different topologies, are one of the most common tools employed [5], [8], [3]. A normalized image of the possible traffic signs is used in all cases as input vector. Although neural networks constitute the main tool used in the classification stage, it is not the only possibility, another huge group of works make use of template-matching techniques. In [9] a normalized cross-correlation between the templates stored in data-base and the possible traffic signs is used, while in [16] a representation of road-sign data, based on extending the traditional normalized cross-correlation approach with a trainable similarity measure, is proposed. On the other hand, in recent times new approaches have been proposed, for example in [17] or [1] where a SVM with Gaussian kernel is used to perform the classification stage.

Finally the tracking stage provides memory to the system so that it takes into account not only a unique punctual instant for detection, but a whole sequence of images instead. Not all the works in this area include this feature, but those in which this approach is implemented reach better results. Among the latter, [4], [1], [14], may be highlighted. All of them make use of an extended Kalman filter [18], and use the 3D-position of the centre of the traffic sign as the state-vector.

III. TRAFFIC SIGNS DETECTION

A. Vision-based traffic signs detection

The aim of the image processing algorithm first step is to detect the precise location of the signs. In order to achieve this goal, an analysis of the shapes obtained from an edge-image is carried out. A Hough transform for straight lines is used to detect triangular, while a Hough transform for circles is applied to detect circular signs as well as the Stop sign, although the proposed method can also be used to detect rectangular or arrow signs, as shown in [2].

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. With the aim of making the detection more reliable, we have chosen to adapt, the two canny-thresholds in a dynamic way, depending on the histogram-distribution of the image. The contours obtained applying Canny method are codified using the chain code. By making use of this codification the area and perimeter are obtained, and it can also determine 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 a certain aspect-ratio constraint. Actually, the Hough transform is only applied to accept contours after being filtered with this kind of restrictions. If all the contours in the image were analyzed the computational cost would be prohibitive, so all those contours that do not meet some requirements, typical of traffic signs, will be removed from the image, so that the computational time is reduced.

A straight line in the image plane can be defined in polar coordinates as it is depicted in (1) with a distance to the origin, ρ, and an angle between the normal line and the abscissa axis, θ.

$$x_i \cdot \cos(\theta) + y_i \cdot \sin(\theta) = \rho \tag{1}$$

Where the parameter space, $p = (\rho, \theta)$, must be quantized and expressed in a 2D accumulation matrix a, whose elements are initially set to zero. So, an element $a(\rho, \theta)$ is incremented by 1 for every contour point (x_i, y_i) in the image-domain, contained in the straight line with parameters (ρ, θ) as expressed in (2), where a precision margin ϵ is introduced to compensate for quantization error when digitizing the image [19].

$$|x_i \cdot \cos(\theta_t) + y_i \cdot \sin(\theta_t) - \rho_r| < \epsilon \tag{2}$$

The aim is detecting three straight lines intersecting each other, forming a triangular sign. Different algorithms have been proposed in order to decrease the computational time of the Hough transform, a multi-dimensional quadtree structure for accumulating is suggested in [20] (coarse-to-fine method), or in [21] 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). In this work a constrained accumulation matrix a is proposed as a method to decrease the computational time, as it can be seen in Fig. 1. The aim is to search for lines only in the shaded areas. The strategy is to apply the Hough transform to every contour, one after the other, hence every straight-line-parameters estimation is calculated by means of (3) and (4), where (x_1, y_1) and (x_2, y_2) are points belonging to the contour under study.

$$\rho = \frac{x_1 \cdot y_2 - x_2 \cdot y_1}{\sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}} \tag{3}$$

$$\theta = arctan\frac{x_1 - x_2}{y_1 - y_2} \quad (4)$$

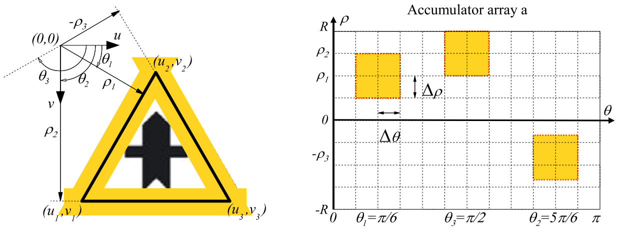

Fig. 1. Constrained Hough transform applied to detect triangular, rectangular and arrow signs.

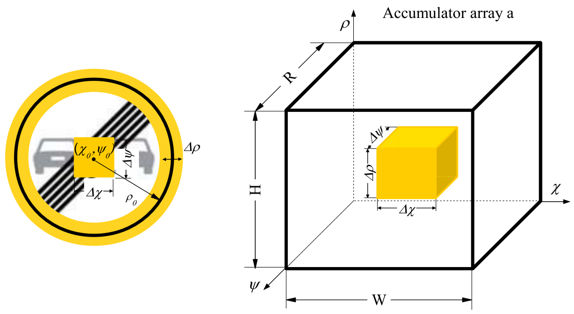

Fig. 2. Constrained Hough transform applied to detect circular signs.

A similar strategy is followed for circular sign detection. Hough transform for circles is applied to detect circular signs and the stop sign too. A circumference in the image plane with center (χ, ψ) and radius ρ can be expressed as (5).

$$(x - \chi)^2 + (y - \psi)^2 - \rho^2 = 0 \quad (5)$$

Where the parameter space, $p = (\chi, \psi, \rho)$, must be quantized. For circumference detection the accumulator a will be a three-dimensional matrix with all elements initially set to 0. The element $a(\chi, \psi, \rho)$ is incremented by 1 for every contour point (x_i, y_i) in the image-domain, contained in the circumference with centre (χ_r, ψ_s) and radius ρ_t as expressed in (6), where a precision margin for the radius ϵ is introduced to compensate for quantization error when digitizing the image [19].

$$|(\chi_r - x_i)^2 + (\psi_s - y_i)^2 - \rho_t^2| < \epsilon \quad (6)$$

The circumference-parameters estimation is calculated using the direction of the contour-gradient under study, as in [10]. The search ranged into accumulator matrix a is constrained, the circumference-parameters are only searched inside shading areas, as it can be seen in Fig. 2.

B. Recognition stage

The selected candidates are classified by means two SVM classifier with Gaussian kernel and probability estimate output. In previous detection stage circular and triangular road signs can be distinguished, so a SVM for up to 56 circular signs and another SVM for up to 44 triangular signs are applied to reduce the complexity of the problem. All candidates are resized to a fixed size of 32x32 pixels to facilitate the features extraction process, and moreover only those pixels that are inside the signal are taken into account by means a triangular or circular mask, thus the feature vector is reduced from 1024 to 798 pixels for circular signs and 532 for triangular ones.

Although the SVM classifiers are binary classifiers, they are easily combined to handle the multiclass case [22], following the one-versus-rest classification algorithm (say, one positive, rest negative). The classifier has been trained using 432 samples per class, which represents more than 43000 samples in total for 100 clases. In the test phase a sign is assigned to the class with highest probability estimate output if this probability exceeds a threshold, but noisy object (no sign) is considered.

C. Tracking

After detecting consecutively an object classified as sign a predefined number of times (empirically set to 3 in this work), data association and tracking stages are triggered. Tracking is implemented using Kalman filtering techniques. For this purpose, a dynamic state model and a measurement model must be defined. The proposed dynamic state model is simple. Let us consider the state vector x_n , defined as follows:

$$x_n = [u, v, r, \dot{u}, \dot{v}, \dot{r}]^T \quad (7)$$

In the state vector u and v are the respective horizontal and vertical image coordinates for the centre of every sign, and r the radius in the image plane. A dynamical model equation can be written like this:

$$x_{n+1} = A \cdot x_{n+1} + \omega_n \quad (8)$$

where A represents the system dynamics matrix and ω is the noise associated to the model. Although the definition of A is simple, it proves to be highly effective in practice. The model noise has been modelled as a function of distance and camera resolution. The state model equation is used for prediction in the first step of the Kalman filter. The next step is to define the measurement model. The measurement vector is defined as $z_n = [u, v, r]^T$. Then, the measurement model equation is established as follows:

$$z_n = H \cdot x_n + v_n \quad (9)$$

In last equation H represents the measurement matrix and v_n is the noise associated to the measurement process. The purpose of the Kalman filtering is to obtain a more stable position of the detected signs as shown in Figure 3.

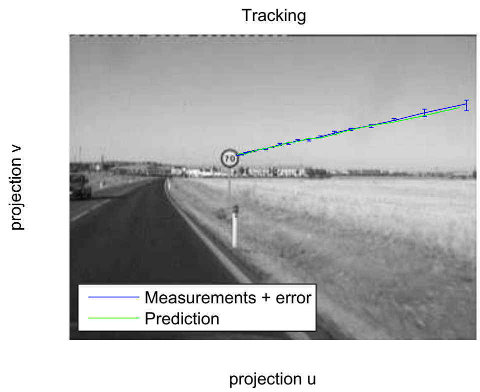

Fig. 3. Measurements and prediction obtained during a tracking of a sign.

D. Stereo refinement

An accurate estimation of the relative position between the vehicle and the traffic sign has an important impact on further stages such as tracking and geometrical discarding. On top of that, it also helps to reduce the probability of considering detected signs that do not pertain to the host road as pertaining to the host road. In order to minimize the error position, the relative distance is computed by using stereo vision. Monocular approaches have to apply some constraints such as flat terrain assumption and previous knowledge about the extensions or the height of the traffic sign, that introduce strong errors in the relative position estimate.

Stereo parameters such as separation between cameras, sensor focal length and images resolution have been defined to reduce the error of the stereo measurements. As described in [23] we use a graphical method to define the sensor setup according to the application requirements. The calibration process is carried out on a supervised fashion in order to minimize the calibration errors. Both images are undistorted and the epipolar geometry is computed. The content of the detected bounding boxes is matched along the epipolar line on the other stereo image by using the ZNCC function (Zero mean Normalized Cross Correlation) as in [24]. The search space can be reduced considering the minimum and maximum ranges. The correlation values are obtained and the values near the optimum are approximated by a second degree polynomial in order to compute the 3D position with subpixel accuracy [25]. This process is illustrated in Figures 4 and 5.

Fig. 4. (Left) Left image and bounding box of the detected speed sign. (Middle) Search space along the epipolar line corresponding to the upper-left part of the bounding box on right image. (Right) Final match on right image.

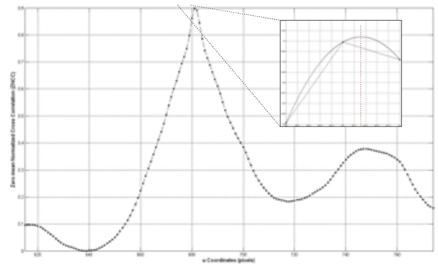

Fig. 5. Correlation function along the epipolar line and second degree polynomial approximation.

Once we have the 3D relative position between the vehicle and the detected traffic signs, a simple discarding process can be applied in order to reject traffic signs that are located too far from the vehicle position (i.e., traffic signs that belong to other roads). However, there are some scenarios like the one depicted in Figure 6, where the 3D relative position is not enough for discarding signs that do not apply to the host road. Some of these cases can be extremely dangerous in the context of intelligent speed adaptation or assistance applications.

The vehicle global position is obtained from the GPS. However, the GPS sample frequency is 1Hz which implies that the system obtains one GPS measurement per each 20-30m approximately (depending on the host speed). As the detection process is carried out at 20 Hz, we apply a linear interpolation between two consecutive GPS measurements. Finally, a global reference for each one of the detected signs is obtained by combining the global position of the vehicle and the relative position between the vehicle and the traffic sign. The global position of the traffic signs is very useful for inspection and inventory tasks, but we propose to also use this global position for solving scenarios like the one described in Figure 6 including V2I communications.

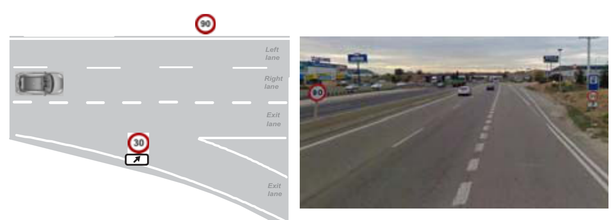

Fig. 6. Left: conflict scenario with two different speed signs. Right: sample image.

E. V2I Communications

In order to improve the traffic signs detection and solve the scenario of Figure 6, we propose a V2I communication system. The system is based on RF wireless sensor motes that will be available in all the traffic signs. Actually, we are using a general purpose platform, Waspmote built by Libelium, and we have installed and set up several motes on traffic signs as transmitters. In addition, we have installed one of them as receiver in our test-car. Transmitter and receiver are shown in Figure 7.

Fig. 7. Left: Waspmote transmitter installed on a signal. Right: Waspmote receiver in the test-car.

Transmitter motes have been equipped with GPS sensors in order to send the global position of the signs to the all cars in the range of coverage. In addition, all the motes have been setting up to transmit a message with the following information at a frequency of 1Hz, according to the GPS updating rate:

- Type of signal: max speed (X Km/h), stop, give way, etc.
- Road name: useful to distinguish between main road and deceleration lane.
- Direction of the movement: increasing or decreasing.
- GPS: coordinates of global position.

Waspmote platforms can be configured with several communication topologies (tree, mesh, p2p), but in any case, transmitter can always send a broadcast message. This characteristic has been exploited by our system to send the message of the traffic signal to all the cars that are in the coverage area. This area ranges from 500m up to 7Km, by using XBee-ZB or XBee-ZB-Pro model of transmitting module. In our case, we have selected the 500m model because is enough for the application purpose.

F. RF mapping

Finally, in order to solve the GPS reception problems, we propose a RF mapping process that helps our process to maintain the traffic sign positioning even when the GPS signal have been loosen.

The RF mapping process that we propose is based on our previous work [26]. It makes possible to estimate the position of the Waspmotes using the distance between them and the vehicle. First of all, the distance is obtained by means of using a path loss propagation model, and then the position of the signs are obtained using the distance and the knowledge of the car trajectory.

A particle filter [27] is used to achieve this aim, which is a sequential Monte Carlo algorithm, i.e., a sampling method to approximate a distribution that uses its temporal structure. A ”particle representation” of distributions is used, in particular, we will be concerned with the distribution $P(X_{bt}|z_{0:t})$ where $X_{bt} = (x_{bt}, y_{bt}, \theta_{bt})$ is the observed traffic sign at time t, and $z_{0:t} = (r_1, r_2, ..., r_n)$ is the sequence of observations from time 0 to time t.

The transition and sensor models, $P(X_{bt}|z_{0:t})$ are represented using a collection of N weighted samples or particles, $\{X_{bt}^{(i)}, \pi_t^{(i)}\}_{i=1}^N$ where $\pi_t^{(i)}$ is the weight of particle $X_{bt}^{(i)}$ (Equation (10)).

$$P(X_{bt}|z_{0:t}) \approx \sum_i \pi_{t-1}\delta(X_{bt} - X_{bt-1}^{(i)}) \tag{10}$$

Firstly, the particles are uniformly distributed around a ”ring” with radius equal to the first range measurement, we make this ”ring” wide enough in order to absorb the signal noise.

Secondly, the particles are not propagated using any motion model since we know that the traffic signs are static, instead we apply a small random noise to the position of the particles in order to avoid that all the particles stay at the same position.

Finally, the particles are updated by the previous actions a_{t-1} and the actual observation z_t. Finally, it is important to highlight that this algorithm does not need to collect a high number of samples to estimate the beacon position.

IV. RESULTS

The results presented in this paper were obtained from video sequences in real traffic performance under different lighting conditions, in sunny or cloudy days, in the rain and at night. We calculate the performance of the whole system over a test set of 30.000 stereo pair of images, which correspond to 80 km road. The accuracy obtained in the detection stage is summarized in the table I, where P (positive) represents the detected signs and N (negative) represents noisy objects (no signs) detected. We can highlight the detection rate obtained, over 95% in both circular and triangular signs, and the low number of false positives obtained, especially for triangular signs.

TABLE I
SUMMARY OF DETECTION RESULTS

	Signs	P	N	detection rate
Circular	207	197	72	95.16%
Triangular	133	130	12	97.74%

In the recognition stage, the results obtained are shown in the table II, where the recognition rate and accuracy obtained, as in the detection, are very high, between 89 and 98%. Moreover we can highlight that more 35 signs that do not pertain to the host road have been detected and recognised, 25 of them have been discarded by means of geometrical constraints using stereo vision, while the rest have been located and discarded thanks to the information of V2I communication system.

Finally, all these results have been obtained by means of an offline process, however, the average runtime obtained, 35 ms with 19ms deviation, would allow real-time performance. A real-time implementation is an improvement consider as future work.

TABLE II

SUMMARY OF RECOGNITION RESULTS

Signs	TP	FN	FP	TN	recognition rate	accuracy
Circular	176	21	5	67	89.34%	90.33%
Triangular	128	2	6	6	98.46%	94.36%

V. CONCLUSIONS AND FUTURE WORKS

This paper presents a complete traffic sign recognition system that works under different light conditions, at day and night. An important aspect to be highlighted is that either the detection algorithms is adaptive, this adaptation is achieved mainly due to two factors, first the use of adaptive thresholds applied to canny algorithm to obtain contours, that change their values depending on the histogram function at any time, and second, the application of Hough transform depending on the information received form every candidate contour. The experimental results in detection indicate that the proposed method is reliable and accurate since it has obtained an average detection rate of 95%, and also can be applied not only for circular or triangular signs but also to rectangular or arrow signs.

Two different SVM model have been proposed to classify signs, and up to 100 different traffic signs have been recognised with high recognition rate. On the other hand, stereo information and V2I communication system is a novel solution to the problem of discarding detected signs that do not pertain to the host road.

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