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Fast Traffic Sign Detection and Recognition Under Changing Lighting Conditions

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Abstract— **In this work a system for traffic-sign detection and classification is shown. It is intended for both prohibition and obligation circular signs and for advertising triangular ones. The system is divided into three stages: first, detection, using the Hough transform from the information of the edges of the image; second, classification, using a neural network, and third, tracking, making use of a Kalman filter, which provides the system with memory. Some results are presented, obtained by real images recorded by only one camera placed on board a conventional vehicle, in sunny days, and also cloudy, rainy ones or at night, in order to show the reliability and robustness of the system. The average processing time is 30 ms per frame, what makes the system a good approach to work in real time conditions.**

I. INTRODUCTION

The traffic-signs detection and recognition systems have experimented an increasing interest in the last times, due to the importance of safety for drivers, occupants and pedestrians. The detection systems constitute an aid to the driver, providing information to him about the signs appearing on the road. For instance, in case the maximum speed limit is overcome, an acoustic signal advising the driver could be activated. Speed-limit signals are the most important in this work as overcoming speed limits is one of the main causes of traffic accidents, so, the first signs to be searched by our system are this kind of signs. Driving-aid is not the only use of these systems, traffic-signs detection and recognition is also used for inventory, as shown in the AUTOCAT project [3]. In this way, localization and classification of traffic signs is automated, also improving road maintenance. There are a lot of works about these topics but they seldom present results under adverse weather conditions, or at night. In this work, the results of a traffic-signs detection and classification system are shown, used for both circular and triangular signs, able to work in real time and showing efficient performance under adverse lighting conditions.

II. STATE OF THE ART

Three stages can be mainly distinguished in traffic-signs recognition systems, as Gravila notes [17]. These stages are detection, classification and temporal integration or tracking. The analysis will be mainly focussed on detection, as it is the most delicate stage.

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A. Detection step

There are two forms of making the detection stage, not incompatible though; segmentation, using colour-information or analysis of the edges, obtained from grey-scale images. The former has two possible lines too, either working with the RGB colour space [9], [13], [16], [32] or working with those colour spaces that are less immune to lighting changes. In outdoor detection, lighting conditions cannot be controlled and so the RGB colour-space is highly dependant on the light. For this reason in all works, in which this space is used, relations between colour-components are used, what, to some extent, reduces this light-dependence. In this sense [20] makes a colour segmentation using a look-up table, generated off-line by a training process making use of a polynomial classifier, so that pixels are labelled as ”red”, ”blue”, ”yellow” and ”uncoloured”. Finally a colour-connected-components algorithm is applied (CCC), creating a database containing information as the perimeter, surface, colour, etc. of the region of interest, although not working in real time and neither providing results working with poor visibility or at night. In the latter type of works the HSI or HSL colour-space is used in order to reduce more the dependency on light [3], [11], [14], [18], [28]. However, the captured image is not completely invariant against changes in the chromaticity of the received light. The hue component changes with shades, climatologic conditions and the traffic sign age as explained by [31]. Some works improving the colour segmentation have been carried out. For example [28] makes a detection based on a robust colour segmentation, followed by a hybrid parallel decision graph to evaluate the segmented regions of relevant colours.

Among the works in which edge-analysis starts from the grey-scale image, there may be highlighted [5], [8], [6], [17], [25], [27] although the detection algorithms are different. Gavrila [17] uses a template-based correlation method to identify potential traffic signs in images; this involves the so-called distance transforms [7] 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, but 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 [5], related to our work, because a variation of the Hough-transform is used [19]. The method used by Barnes is based on [24], 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-

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image for different radii. Doing so, the method is able to detect only circular signs, more specifically, it is tested with 40 and 60-speed signs in real time performance. In order to detect triangular, square and octagonal signs Loy has used a similar technique in [25] increasing the computational cost so it cannot work in real time. In none of both works the system is tested in the rain or at night.

Comparing the methods based on colour segmentation with the ones based on shape-analysis it can be concluded that colour provides a faster focussing on the seeking-areas, but in practice precision is lower, due to the fact, for example, that blue and red colour spaces might overlap in those signs with white predominance, as in the end of speed limit ones, and there may arise problems in segmentation. Besides, as it has been already said, the measurement of the colour values can change considerably with lighting conditions. Moreover, region-growth methods that do not have information about the model tend to produce undesired problems of loss of colour information. In conclusion, those methods based on shape analysis are more robust against changes in lighting conditions.

B. Classification step

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. This is a much less critical step than detection, that is why in most of the works similar recognition methods are used. Neural networks, in their different topologies, are the most common tools employed. A map of the Kohonen is used in [26], while a cellular neural network is used in [1] able to classify triangular and circular traffic signs, but the most commonly used topology is the backpropagation neural network used in [2], [13], [22], the input to the neural network is a normalized image containing the regions of interest previously detected, for example in [2] the image is 18x18 pixel-size, fifteen neurons in the hidden layer and three output neurons, so it can only distinguish between speed-limit, no-speed-limit sign and no-sign. Finally, another topology, widely used, is the radial-base neural network (RBF), used in [17], [23] and, as in the previous cases, a normalized image of the possible traffic signs is used. 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 [27], [5], [29], make a normalized cross-correlation between the templates stored in data-base and the possible traffic signs. For instance, Barnes applies the cross-correlation over a 5x5 window between the sign templates and the candidate signs. The classification is applied only to two different speed-limit signs and only with three different radii for the search.

C. Temporal integration step

The last stage is the time-integration one, it enhances the reliability of the previous ones as it consists in providing the system with memory so that it takes into account not only a unique punctual instant for detection, but a whole sequence of images instead. To do so, the system must include the possibility of tracking. Not all the works in this area include this feature, but those in which this approach is implemented reach better results. Among the latter, [3], [17], [27], may be highlighted. All of them make use of an extended Kalman filter [21], and use the 3D-position of the centre of the traffic sign as the state-vector.

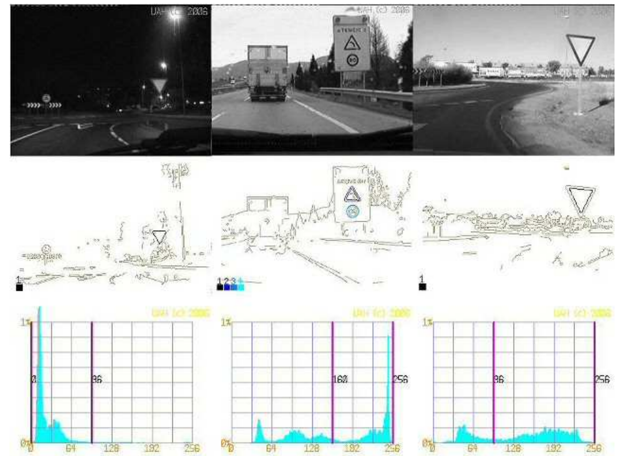

Fig. 1. Some images captured at night, in the rain and in a sunny day, with their corresponding histograms, in which threshold levels used to obtain the contour-image are shown. Contours meeting the restrictions are highlighted; Hough transform will be applied to them.

III. DETECTION

In this stage an analysis of the shapes obtained from an edge-image is carried out. In order to detect circular signs Hough transform for circumferences is used, while for triangular-signs detection the Hough transform for straight lines is used. The method works at day and night without the need of changing the algorithm, what is used thanks to the use of dynamic threshold-levels which change their values depending on the histogram distribution of the captured frame every time.

A. Contours Information

The algorithm used for edge detection is Canny method [10]. This method preserves contours, what is very important for detecting traffic signs using shape information because they are usually closed contours. The Canny operator uses the so-called ”hysteresis” thresholding. 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, so, the histogram has been divided into eight regions and a pair of threshold levels has been assigned to each one of the regions. In this way, the threshold levels assigned to the region with a wider value-distribution will be used, as it can be seen in figure 1. With this approach, it is possible to use the same algorithm either under good visibility conditions, in the day, or under less favourable conditions, at night, or in the rain.

The Hough transform could eventually reach a high computational cost if all the contours in the image were analyzed. However, all those contours that do not meet some requirements supposed to be typical of traffic signs can be removed form the image.

The contours obtained applying Canny method are codified using the "chain code" [15]. By making use of this codification the area and the 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. They must also fulfil a certain aspect-ratio constraint, showing similar width and height. Circular traffic signs, including stop one, as well as triangular ones, meet these restrictions with high probability, as can be seen in figure 1. Hough transform is only applied to accepted contours after filtered with the aforementioned restrictions, so that the computational time is reduced.

B. Hough Transform

The classical Hough algorithm can be easily extended to find any curves in an image that can be expressed analytically in the form $f(x,p) = 0$ [4]. Here, x is a point in the domain of the image and p is a parameter vector.

Hough transform for straight lines is applied in order to detect triangular signs. A straight line in the xy-plane with a distance to the origin ρ and the angle of the normal line to this straight line passing through the origin, with the abscissa axis θ can be expressed as (1).

$$x \cdot \cos(\theta) + y \cdot \sin(\theta) = \rho \tag{1}$$

Where the parameter space, $p = (\rho, \theta)$, must be quantized. If the origin of the co-ordinate system is placed in the centre of the image, the largest possible distance between a point in the image and the origin is R. Hence, in order to generate any straight line of an image, ρ may be varied between $-R$ and $+R$, and θ may be varied between 0 and π radians. The parameter-space is quantified and expressed in a 2D accumulation matrix A with dimensions mxn, where m is the number of values assigned to ρ and n is the number of values assigned to θ. For straight lines detection all the elements of A are initially set to zero. So, an element $A_{rt}(\rho_r, \theta_t)$ is incremented by 1 for every feature point (x_i, y_i) in the image-domain, contained in the straight line with parameters (ρ, θ) as expressed in (2), and as shown in figure 2, where a precision margin ϵ is introduced to compensate for quantization error when digitizing the image [30].

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

The aim is detecting three straight lines intersecting each other, forming a 60 degrees-angle. It must be observed that, as long as the number of straight lines intersecting each other might be very large if the Hough transform was applied to the whole image, more than the actual triangles existing in the image would be detected. Using Hough transform neither the beginning nor the end of a straight line is known. In order

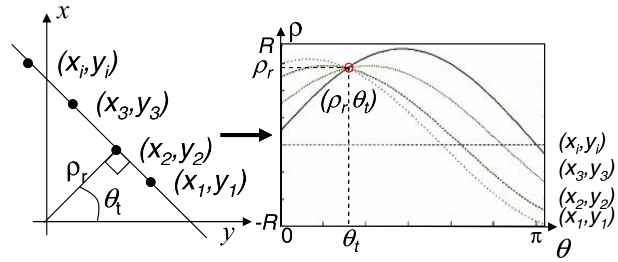

Fig. 2. Hough transform for straight lines.

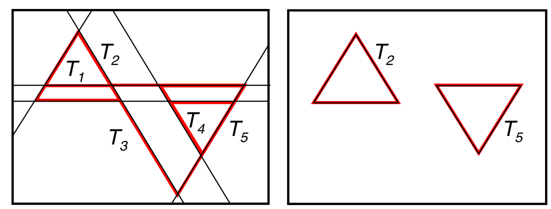

Fig. 3. Straight lines detected using Hough transform, applied to the whole image (left) applied to each contour, one by one (right).

to overcome this handicap in this work the strategy is to apply the Hough transform to every contour, one after the other. In this way, only those triangles existing actually in the image are detected, as shown in figure 3, reducing the computational time too.

A similar strategy is followed for circular sign detection. Hough transform for circumferences is applied to detect circular signs and the stop sign too. Although the stop sign is octagonal, the difference between octagonal and circular signs is very slight, and the former ones are also accepted. A circumference in the xy-plane with center (χ, ψ) and radius ρ can be expressed as (3).

$$(x - \chi)^2 + (y - \psi)^2 - \rho^2 = 0 \tag{3}$$

Where the parameter space, $p = (\chi, \psi, \rho)$, must be quantized. The accumulator matrix A is the representation of the quantized parameter space. For circumference detection the accumulator A will be a three-dimensional matrix with all elements initially set to 0. The element $A_{rst}(\chi_r, \psi_s, \rho_t)$ is incremented by 1 for every feature 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 (4), and as shown in figure 4 where a precision margin for the radius ϵ is introduced to compensate for quantization error when digitizing the image [30].

$$|(\chi_r - x_i)^2 + (\psi_s - y_i)^2 - \rho_t^2| < \epsilon \tag{4}$$

For circular-objects detection the same criteria are followed as in the case of straight lines. Hough transform is applied contour by contour, so that those contours corresponding to other shapes but not signs do not affect the detection of the latter ones, so, feasibility is increased too and computing time is reduced considerably, as with the classic Hough transform all the pixels are analyzed as possible centres and the threshold must be fixed. This implies that

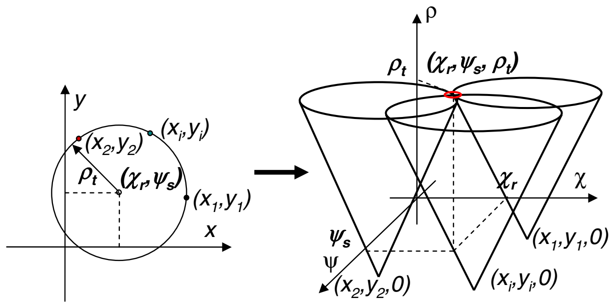

Fig. 4. Hough transform for circumferences.

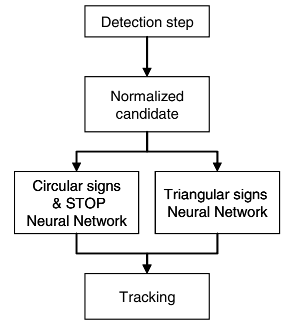

Fig. 5. Block diagram of the classification stage.

more circumferences than the real existing ones are detected. In order to avoid detecting inexistent circumferences the analysis of every contour is performed and the Hough transform is applied only to the points belonging to the contour under study. Hence, the information of a contour obtained already in a previous stage is used and the centre of the circumference is searched in the environment of the centroid of the corresponding contour. In this way the number of iterations is considerably lowered without loss of reliability. On the other hand, a thresholding can be done, adapted to every contour; if the contour has a large amount of points its threshold is higher than if there are less points in it. With this, seeking circumferences only with certain radius, as it happens in [5] is avoided. All these considerations make detection time to be very short, making the system able to work at a processing-speed between 5 and 50 frames per second, depending on the number of contours detected.

IV. CLASSIFICATION

Making use of the information obtained in the detection stage, where it is known if the possible signs are circular or triangular ones, two different neural networks have been implemented for recognition. One of them identifies whether it is a triangular sign or not, and its type, and the other one recognizes the circular signs, including the stop-one. Both of the neural networks are backpropagation neural networks, where the input to it is a 32x32 pixel-size normalized image of the candidate sign. Every type of sign, wanted to be detected, has a normal distribution probability-density function, centred in a neuron and with a deviation $\sigma = 1$. To identify a sign, a correlation between the values of the output-layer neurons and the normal distribution is carried out, and depending on which neuron the maximum is reached at, and if it overcomes a certain threshold, it will be classified as a sign, or else as no-sign. Besides, the value of the correlation indicates the probability that the detected sign is a correct sign. The steps are shown in the block-diagram in figure 5.

It must be noted that the networks have been trained to recognize the speed-limit and end-of-speed-limit, stop, forbidden-overtaking and end-of-forbidden-overtaking signs for circular ones, while for triangular signs, the give way sign, and dangerous-curves advertisement are considered. Real time tests have been carried out working with a database, from which the system is able to distinguish among more than a thousand signs, reaching a 99% classification-rate.

V. TEMPORAL INTEGRATION

Once the sign has been detected and classified it is necessary to track it, so that the system is provided with memory and it is not necessary to do the classification with all the frames, and once the candidate is classified the type of sign would be shown if the recognition was positive, or else it would be labelled as no-sign in case the recognition was negative, in order to reduce the seeking time in next frames. To perform the tracking a Kalman filter has been implemented, this filter makes an estimation of the evolution of the system and compares it with the actual output; in this way its estimation is improved as it keeps on executing, making the algorithm to be recursive. Tracking is performed with circular and triangular signs, and in both cases the state-vector is (5).

$$x(x_k, y_k, r_k)^T \tag{5}$$

Where the components (x_k, y_k) of the state-vector are, for circular signs, the centre of the detected circumference, and for triangular ones the centre of the circumscribed circumference, while the component r_k is the radius of these circumferences. An example of an application of Kalman filter is shown in figure 6, where it can be seen how a tracking of a sign under different lighting conditions is done.

VI. RESULTS AND CONCLUSIONS

A real time-algorithm for traffic signs detection and recognition has been shown. The algorithm is able to detect any kind of signs but the informative ones, using a similar technique for all of them, Hough transform, making the algorithm very robust and reliable. The system works with one only camera mounted on the windscreen of the car, as shown in figure 7. Several tests have been conducted, placing the camera in different positions on the windscreen, and it has been concluded that the placement of the camera is not decisive, but orientation is, thus affecting the quality of detection. The best arrangement is to place the camera pointing towards the same direction and sense of the car so that signs are seen orthogonally to the egomotion direction

Fig. 6. Traffic sign tracking under different lighting conditions using the Kalman filter. From left to right and up to down: end of forbidden overtaking at night. Same signal with rain drops on the car windscreen. Left bend warning sign and speed limit sign in a cloudy day. Give-way sign in a sunny day.

Fig. 7. One camera mounted on the windscreen of the car.

and thus suffering the least possible distortion. Should a circular sign be captured non-orthogonally by the camera, it would be seen as an ellipse in the image and would not be so neatly detected. However, Hough transform can be extended to ellipses, but it would be necessary to add two new parameters in the parameter-space with respect to the transform for circumference used in this work. This technique has been tested in fact, and it was noticed that the average processing time was 2 seconds, so the system could not operate in real time. It is important to realize that detecting circumferences but not ellipses is in fact a simplification of the method, but it does not imply a poorer performance at all. On the contrary, an elliptical shape in the image captured, if it happened to correspond to a sign, would be placed with high probability in another road with other direction, for instance in a crossroads. So, only those signs detected as circular are placed in our road in the egomotion direction.

The system has been empirically tested under different lighting conditions, in sunny or cloudy days, in the rain and at night, as it can be seen in the sequence of images in figure 8. An important aspect to be highlighted is that either the detection algorithms, or the classification and tracking ones are the same in every case because they are adaptive. 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

TABLE I

RESULTS OF TEST MADE.

traffic sign	amount	detecting	recognition
speed limit	435	97.2%	98.5%
warning	312	94.3%	97.2%

depending on the information received form every candidate contour. Tracking, using the Kalman filter improves clearly the computational time and also provides the system with memory what makes possible classifying a sign only once. On the other hand, recognition stage, solved by using a neural network, is eventually less critical than detection one; speed limit and warning traffic sings have been chosen in order to test the system, although it can be extended to the rest of traffic sings. The results of this test are shown in table I.

As future work, it would be of high interest to integrate this system with a positioning one as the GPS, in order to be used for inventory and sign maintenance. It would also help distinguishing whether the detected sign is aimed to the driver carrying the system.

ACKNOWLEDGEMENTS

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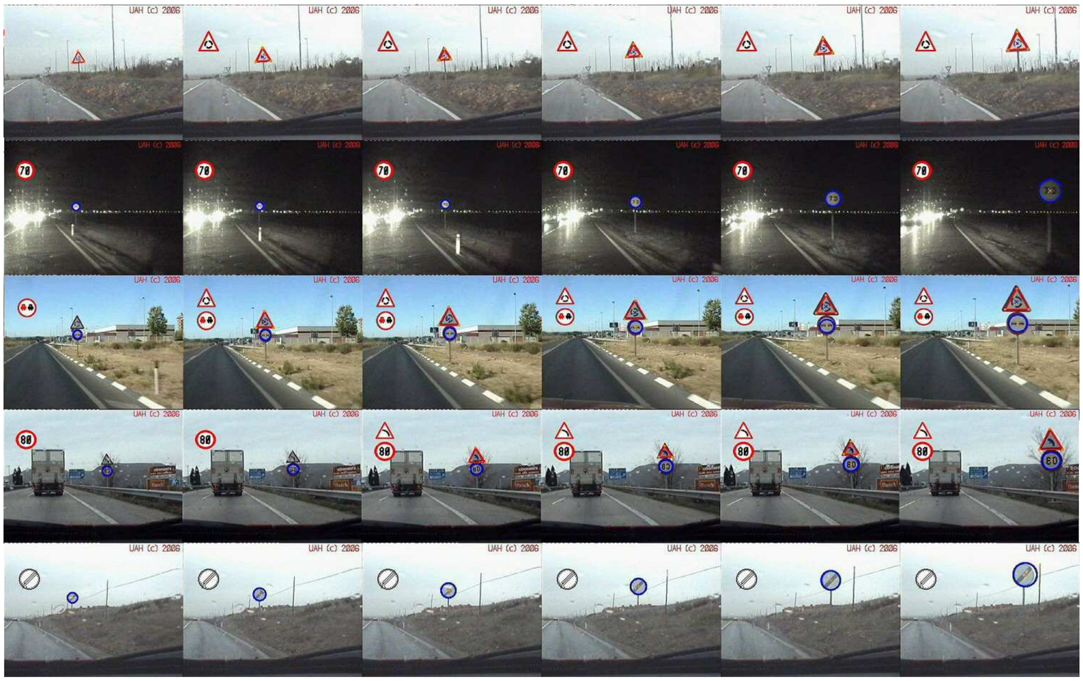

Fig. 8. Sequence of real road images under different weather and light conditions, where circular and triangular signs are detected.

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