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A Prototype for Automatic Road Sign Recognition and Detection

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Abstract—This paper deals with the extraction of part of the visual information presented in streets, roads, and motor ways. This information, provided by either traffic or road signs or route-guidance signs, is extremely important for safe and successful driving. An automatic system that is capable of extracting and identifying these signs automatically would help humandrivers enormously; navigation would be easier and would allow him or her to concentrate on driving the vehicle. The system would indicate to the driver the presence of a sign in advance, so that some incorrect human decisions could be avoided. A deformable model scheme allows us to include the knowledge used while designing the signs in the algorithm and is used for theirdetection and identification. Two techniques to find the minimum in the energy function are shown: simulated annealing and genetic algorithms. Some problems are addressed, such as uncontrolled lighting conditions; occlusions; and variations in shape, size, and color.

Keywords—Advance driver-assistance systems (ADASs), deformable models, intelligent vehicles, traffic sign recognition.

I. INTRODUCTION

DRIVERS receive a lot of visual information, of different kinds, while driving a car. It can be stated that thisinformation is related to two main goals: safety and successful driving. These goals are achieved through two driver's tasks: piloting and navigation. The first task takes into account visualinformation, in order to avoid obstacles while driving the vehicle in the correct lane and at the right speed: position and trajectory of others vehicles, pedestrians' movement, road lanes, and status. Other visual information, such as landmark detection and recognition, are related to the success of the driving and to reach the destination, which is the goal of the driver's navigation task. Advance driver-assistance systems (ADASs) are designed to help (or substitute) human drivers in these two tasks.

An ADAS with the automatic ability to extract and identify these signs would help human drivers a great deal, making the navigation task easier and allowing him or her to concentrate on driving the vehicle. For example, the system would indicate the presence of the sign to the driver in advance, thanksto the greater focal length of the optics. Furthermore, some human decisions can be limited, such as exceeding the maximum speed allowed, trying to pass another vehicle in a dangerous zone, or parking the vehicle in a forbidden area. It can be helpful for other ADAS, such as the adaptive cruise control, to predict the road shape (i.e., curve to the right). Finally, it will be still necessary when the future intelligent vehicles would be automatically controlled.

This paper is focused, differing ones published previously, in dealing with these degrees of freedom. Special emphasis is given when dealing with a sign's partial occlusions. In addition, the problem of lighting changes and shadows are also described. Finally, the restriction where the sign has to be perpendicular to the camera is not applied. Thus, the ADAS presented in this paper is capable of detecting traffic signs independently of their appearance in the image

The recognition process is triggered by an image's color analysis if some object of an accurate color is found. To accomplish this task, some energy functions, related to color and shape, are calculated and its minimum is found. The minimum will match the best fit of the traffic sign model to the imageFig. 1. Some difficulties for the detection of road signs. Due to the fact that lighting cannot be controlled, there are either (a) reflections and (b) shadows or (c), (d) their appearance changes during the day. There are either (e), (f) other objects that generate occlusions or (g), (h) have the same color. They can be (j) deformed in the image; color and shape depends on age and physical condition

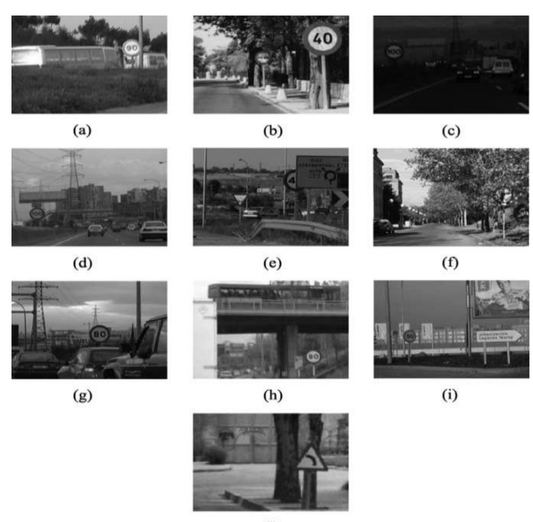

Figure 1: Some of the difficulties in road signs

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II. STATE OF THE ART

The most important research for detection will be presented first, followed by the work involving recognition.

A. Sign Detection

The criteria to classify traffic sign detection research is whether or not it uses the color information of signs.The object borders presented in the image are obtained and enhanced by a distance transform (Chamfer distance). To detect the sign, the models are correlated with the image. In [14], edges' orientation are used to look for circular and triangular signs the images are transformed using wavelets and are classified using a Perception neural network (NN). Some authors use standard color spaces. As lighting invariance is one of the main problems, they work with relations between the red, green, blue (RGB) either color components or subgroups within this color space

The drawback is the higher computational cost of these systems. To conclude, color is an important piece of information to detect traffic signs, but the color variance is very high, not only because the weather conditions changes the color of the same sign, but also because the presence of other objectscan produce shadows, changing the color of some parts of the sign. Finally, each sign has a different color, depending on its age and physical condition. It is very difficult to obtain a global model for all possibilities, but if the algorithm deals with partialocclusions, the color-segmentation step, although important, is not as decisive as was believed until now. The presence of an object partially occluding a sign would produce the same effect as would a bad segmentation and occlusions, except for motorways,where occlusions are more difficult due to the sign size and location, but is a frequent case on roads and almost always within cities.

B. Sign Recognition

Once the sign has been detected, the recognition is performed. The outer border is coded; after a complex log-mapping transform (immune to scale and rotation) a fast Fourier transform (FFT) is done. For the final classification, matching with a spectrum database is carried out

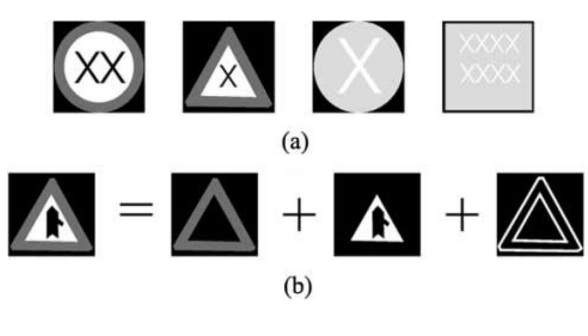

Figure 2: Sign models and *a priori* knowledge. (a) Initial model represents a sign at a fixed distance, perpendicular to the optical axis, located at the center of the image. (b) Prior knowledge indicates that a sign is the sum of a colorborder, an achromatic (either white and/or black) inside part, and a shape.

III. TRAFFIC SIGN MODEL

Traffic signs were designed to be easily spotted by human drivers. The knowledge of their design can be used by the sign detection step incorporating this prior knowledge into the deformable model.

Assumptions

1) Initial model M, which is the sign with a fixed area, locatedin the center of the image.
2) Deformable model M(Z), which is obtained from theprevious model through the deformation parameters. In the case of circular signs, position, horizontal, and verticalscale, and for triangular and rectangular signs, rotation isan additional deformation parameter.
3) Likelihood probability density function (pdf) P(I Z),which means that the probability of the deformation set Z occurs in the image I.
4) Search algorithm to find the maximum of the *a posteriori*probability P(Z,I).

C. Probability Functions

The likelihood function has to be designed to reach its maximum value when the deformed model matches image. Due to shadows, occlusions, weather conditions, etc., the model has to incorporate as much information as possible. As can be seen in Fig.2, prohibition signs are circular and the border coloris red and white inside with the iconography information black. Warning signs are the same, but with triangular form. Information signs are rectangular and blue, with the iconography information white, while obligatory signs are circular. Thus, the model has to consider the following.

1) Color distribution of the sign, meaning that every sign has a color part (either red or blue) with achromatic (either black and/or white) information inside. This will be reflected in terms of color and chromatic energy.

2) Another piece of information is related to shape andwill be reflected in terms of gradient and distance energy. Both energies measure the same piece of information—how the shape of a sign candidate matches the real sign. However, the distance energy has some value, although the sign candidate does not match the real sign, while the gradient energy has a high value when there is a good match and nearly zero when there is not.

D.Decision Tree

Color and shape are the key features for the detection stage and can be used to split the problem into different sub problems (Fig. 4).

In this way, the first decision is taken depending on the color presented (either red or blue). For every color, the possible shapes are different: circular and triangular for red and circular and rectangular for blue.

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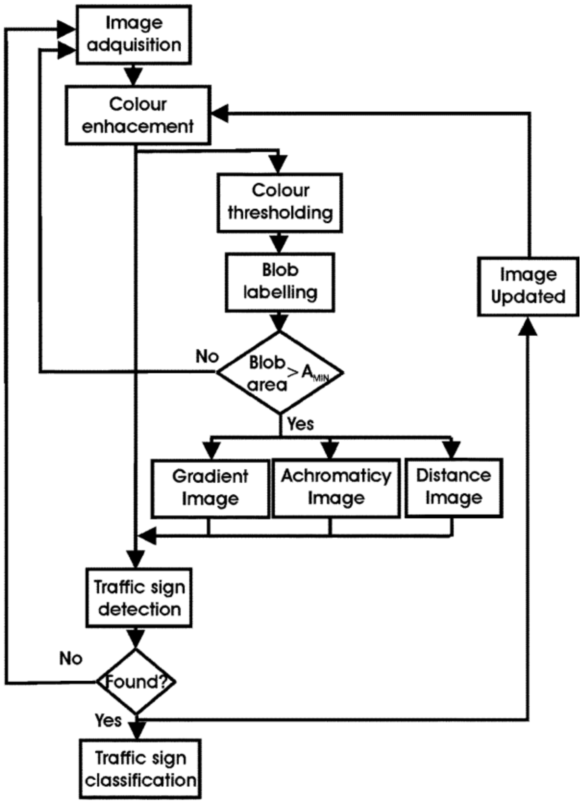

Figure:3 Algorithm description. The color information is used not only to recognize the sign, but to trigger also the process. If there are regions with one of the main colors(red and blue), the energy functions are calculated and are the inputs to the detection module. If any sign is found, the classification is carried out. Also, the algorithm checks if another sign is present. In order to accomplish this task, the images are updated and the blob analysis is performedagain.

IV. ENERGY FUNCTIONS

A. Color Enhancement

The use of color analysis is essential because traffic, road, or vertical signs are designed using colors to reflect the sign's message. For this reason, the chosen colors stand out from the environment. The problems are well known: lighting variations and color degradation due to the age of the traffic sign. HSI color space has been chosen for the color classification since it gives different pieces of information in every component. The first task is to enhance the desired color in the image. This is accomplished by two lookup tables (LUTs) for every color: one for the hue and the other for the saturation component (Fig. 5). The sign's red color has either very low or very high hue values (0 red, 85 green, 170 blue, 255 red). At 0 and at 255, the maximum values are found; they decrease following a ramp until they reach a value of 0 for two different hue values. The blue-hue LUT has its maximum at a certain value and again decreases for two different values. As for the saturation component, its value will be higher, as much color as the sign pixels contain. The LUT will follow a ramp until it reaches a saturation value; from that point on, it will have the maximum value (Fig. 5). Once both LUTs are applied, the images are multiplied and normalized tothe maximum value of 255. The values have been chosen from a representative set of images, keeping in mind different weather conditions. A human operator has segmented the signs and the hue and saturation values of the pixels belonging to the signs were stored. The histograms are shown. The chosen values contain 99% of the pixels and are presented in Table I. It is important to emphasize that a correct classification will not be necessary because occlusions will be considered. The results of color enhancement can be observed, where different types of traffic signs are shown. There is a thresholdingof this image and the obtained blobs are analyzed. If one is greater than an area threshold, a possible sign can be in the image; otherwise, another image would be acquired and the enhancement repeated. This method has been used instead of thresholding and components performing a logical AND operator has been used to form a binary image because errors produce by the use of rigid limits, as in thresholding, are meant to be avoided.

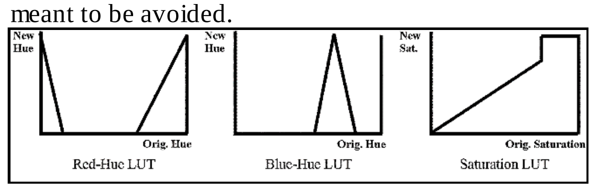

Figure 4: Color LUTs. The color enhancement is accomplished by two LUTs for the hue and saturation components. After applying the LUTs, the images are multiplied and normalized to 255 values.

TABLE I
HUE AND SATURATION VALUE FOR THE COLOR CLASSIFICATION

	Hue min		Hue max	Saturation min	
	95%	99%		95%	99%
Red signs	8-230	11-224	0 (255)	36	23
Blue signs	131-141	128-143	137	111	84

B. Chromatic Image

The other energy functions have to be obtained once a sign can be presented in the image. The chromatic image represents the inside part of the sign that is either white and/or black

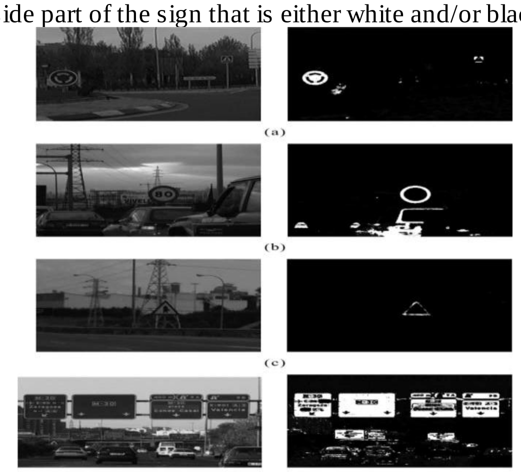

Figure 5:Color enhancement. (a) Circular blue signs, (b) circular red signs,(c) triangular red sign, and (d) rectangular blue signs.

As it is a penalty function, the gray color needs to have a low value and the others a high value. The saturation component gives the amount of white color presented in the color of a pixel, but it is very sensitive to noise at low values (black), as shown in Fig. 6

Figure 6:Chromatic image. (a) Although saturation gives the amount of whitecolor, it is very sensitive to noise. (b) Because of this, the error to the gray colorhas been used.

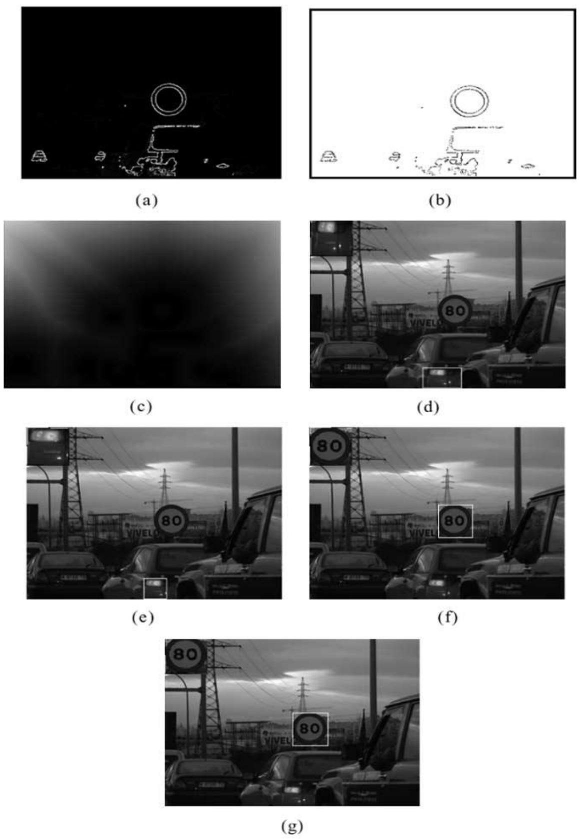

Figure 7: Energy functions. From the color image, (a) the gradient, (b) the edges,and (c) the distance to them are obtained. (d) And (e) If only the color or gradient information are used, the detection fails. (f) If the color and chromatic energiesare considered, the sign is detected. (g) If the four energies are used, the sign isdetected more accurately

V. Sign Classification

There are five main problems for a correct sign classification.

1) As shown in Fig. 8, the number of possible signs is quite big.
2) An additional problem is that the same sign has a slightly different pictogram from one country to another.
3) Occlusions have to be considered.
4) Lighting conditions are very different.
5) There are difference in scales.

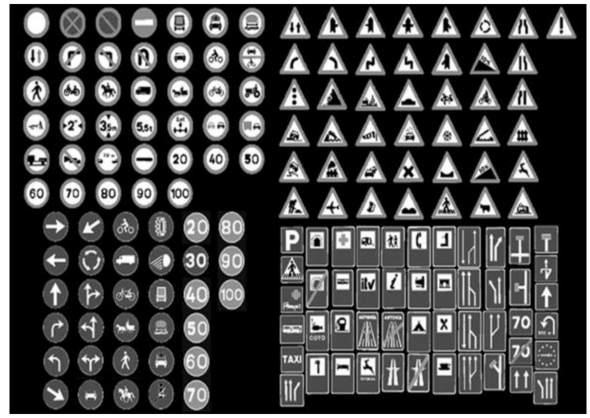

Figure 8:Traffic signs database for red and blue signs

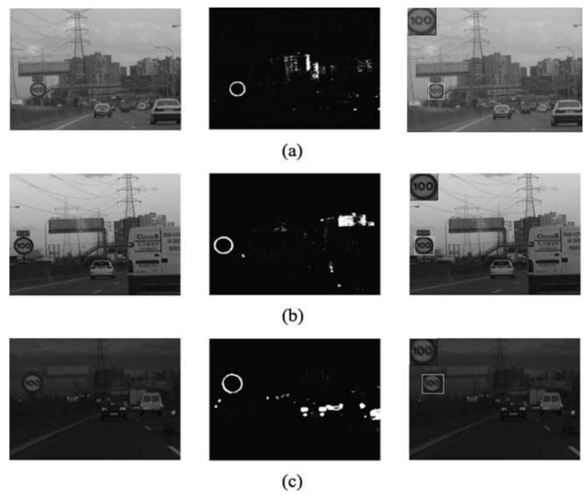

Figure 9: Invariance to lighting conditions is critical to detect the signs.(a) Overcast day, (b) at dusk, and (c) at night. The center column is the result of enhancing the red color and the right column is the detection result.

VI. Results

The method presented in the paper is invariant under lighting changes. In this way, the same sign, under different weather conditions (an overcast day, at dusk, and at night), is shown in Fig. 9. The pixels belonging to the sign are correctly classified and the sign is detected. Other lighting conditions as reflections and shadows are shown

VII. Conclusion

In this paper, an algorithm to detect and recognize traffic signs has been proposed, although the algorithm that has been used for traffic signs can be widely used for other kind of objects. The known difficulties that exist for object recognition in outdoorenvironments have been dealt with. For this reason, the system is immune to lighting changes, occlusions, and object’s deformation being useful for ADASs.

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