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Automatic evaluation of traffic sign visibility using SVM recognition methods

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Abstract: We present an automated low cost method for evaluating the visibility of traffic signs. For this propose we define a parameter which evaluates how road signs are seen by drivers at night. Thus, the evaluation is done from inside a vehicle, using the headlamps as light sources and a colour digital camera to capture the signs in sequences acquired as we approach them. The captured frames are then automatically processed with a software which allows us to detect and recognize the signs using Support Vector Machines (SVM) as a novel classification technique. Finally, a parameter for measuring the visibility of signs is obtained from the sequence. As example, this technique has been applied successfully over three different signs with three different degrees of surface deterioration.

Key-Words: - Traffic sign visibility, luminance, brightness, reflectivity, Support Vector Machines (SVM), detection and recognition.

1 Introduction

Current methods for evaluating the reflective material used for traffic signs consist on visual inspection, measurement of retroreflectivity with a hand-held retroreflectometer, or systematic periodic replacement of the signs irregardless of their deterioration. These methods are too subjective or too tedious, time consuming and expensive.

At present there exist only a few automatic methods for evaluating the sign deterioration "on road" (while traveling along the road) [1],[2]. These methods use typically a CCD camera which takes continuously images from the road where the signs may be located. The automated method from [1] determines the retroreflectivity while the method proposed in [2] measures the relative luminance at night. The retroreflectivity, defined as the ability to reflect incident light back towards the reference source, is a more standardized parameter for evaluating the sign deterioration [3] but is necessary to know for each measurement the distance and relative orientation and position between light source, sign and camera. The influence of other light sources is overcome by triggering the camera with a flashed reference light source. The relative luminance measured in [2] is obtained from the direct measurement of the value of one or average values of the R,G,B buffers of the digital (in this case color) camera. In the method [2] the signs are illuminated at night with the vehicle headlamps.

For a low cost and a more realistic way to evaluate the visibility (meaning the degree of being perceptible by the eye) of the signs, we also propose to do the measurements at night, illuminating the sign with the vehicle headlamps. In this way, successive images are captured from the illuminated sign with a digital camera at different vehicle-sign distances.

For this purpose we need to extract traffic signs from the captured images. This task may be very tedious if it is done manually. Thus, an automated system for sign detection and recognition is necessary and in our case, the system is implemented using Support Vector Machines (SVM). Furthermore, the recognition of the specific sign will give us information of their size which results an alternative data to obtain the distance between the camera and the sign.

2 Proposed visibility measurement

The value of the average gray level (meaning the sum of the value of the R,G,B buffers) of the image of the sign ($\overline{n}_g$) is directly related to the value of the average luminance (L) on the whole sign surface [4]. This relation depends on the camera settings (exposure time, aperture number, pixel size, detector sensitivity,…) and a proportionality constant which relates the value of the gray level with the luminous flux on the sensor (lm/(gray level · s^{-1})). Thus, if the camera settings are constant then, by measuring the average gray level of the sign we obtain the average luminance of the sign multiplied by a constant factor (C, with units cd/(m^2·gray level)):

$$L = C\,\overline{n}_g \quad (1)$$

On the other hand, the gray level (and the luminance) depends on the illumination of the sign. If we know the illuminance (E) on the sign (luminous flux which reaches a surface element) we can obtain the reflectivity (R), defined as luminance divided by the illuminance:

$$R = C\frac{\overline{n}_g}{E}, \quad (2)$$

units of [R]=cd/lm, [L]=cd/m^2, [E]=lm/m^2.

Finally, depending on the type of surface, the illumination and observation angle on the surface may have a big influence. For perfect diffuser type surfaces there is no influence, but for mirror type there is a maximum of the reflected luminance in the specular direction, and for retro reflective surfaces there is a maximum of the reflected luminance in the direction of the incident light. The current traffic sheeting material is retro reflective showing a high brightness when illuminated at night.

To avoid the influence of the illumination and observation angle, the measurement can be done in retro reflective conditions, what means that the sign is illuminated and captured with the camera and the light source aligned on the same direction to the sign surface. In this condition the retroreflectivity is measured (whenever E is known).

Although there are other four causes to considerate which will affect the measurements independently of the sheeting material of the sign:

- By approaching with the car to the traffic sign the illuminance of the sign increases with the square of the light source-sign distance.
- The intensity within the solid angle which comprises the headlamps is not uniform; this provokes a change in the illuminance of the sign when we are too close.
- The change in the retro reflective conditions.
- The influences of uncontrolled light sources illuminating the sign.

These influences are difficult (expensive) to overcome, but if done [1] we may obtain a parameter what is more related to the real surface deterioration, namely the retroreflectivity.

Despite these influences, by measuring the luminance we are measuring what the motorist actually sees (under the same conditions). The luminance is the measurable parameter of the brightness (subjective attribute from what the human eye sees). Thus, we detect the deficient visible signs whatever the causes may be.

As a matter of fact, all the above factors are going to affect the measurement of the luminance causing a strong fluctuation by the measurement of the gray levels at different vehicle-sign distance (d).

A realistic criterion for measuring the sign visibility is necessary to take account all the above factors. Thus, we will take measurements of the average gray level for different distances d.

We may not have a direct measurement from the distance d at which each image of the sign is taken, but we may know the sign real area (S). For $f/d \ll 1$ (f focal length of the objective), we can obtain d from the sign area from the relationship:

$$d^2 \cong \frac{S}{S'} f^2, \quad (3)$$

being S' the area of the image of the sign.

The proposed parameter (V) to measure the visibility of the signs is the average value of the average gray level of the pixels forming the sign image obtained at different distances d along the road, divided by the average value of the distances d at which the sign images are taken:

$$V = \sum_i \frac{(\overline{n}_g)_i}{d_i} \quad (4)$$

where i indicate the image number i. This parameter is then a measurement of the visibility in a interval of vehicle-sign distance, and for a given vehicle.

3. Sign detection and recognition

To measure the parameter V in an automatic way, we need to detect and extract the sign from the captured image. If the distance light source-sign is not directly known, then we can obtain it through the real sign area, for example, by recognizing the sign. For this purpose, we developed a software which was applied successfully over Spanish traffic signs [5]. The system performs the following tasks briefly described.

3.1. Sign Detection

Different color spaces have been used in the literature to isolate traffic signs in outdoor environments. The difficulties that we find at this point are related to illumination changes and the possible deterioration of the signs.

Two components of the HSI color space, Hue and Saturation, were used in our system to segment the signs because both components give us all color information and are invariant enough to lighting conditions. Unfortunely, Hue and Saturation are not able to extract white signs from the images. For this reason, a chromatic and achromatic decomposition is implemented in a similar way to the method described in [6].

Since traffic signs present habitual colors (red, blue, white and yellow) after segmentation process, each pixel of an image may be classified into any of the four colors above mentioned. So, the digital image is decomposed into similar components. It is a key step in the robustness of the whole system.


(a)


(b)


(c)

Fig.1. Segmentation process. (a) Original image; (b) segmented regions belong to a red traffic sign and red noise objects; (c) results after selection process.

In order to eliminate noise blobs with the same color as the traffic signs, we pay attention to their size and aspect ratio. Traffic signs present different sizes according to the distance to the camera, however the variation of size is limited. For this reason, we can filter those objects with an area out range. On the other hand, traffic sign shapes have aspect ratio near unity and we can discard blobs with unsuitable aspect ratio. So, a selection process is implemented by size and aspect ratio.

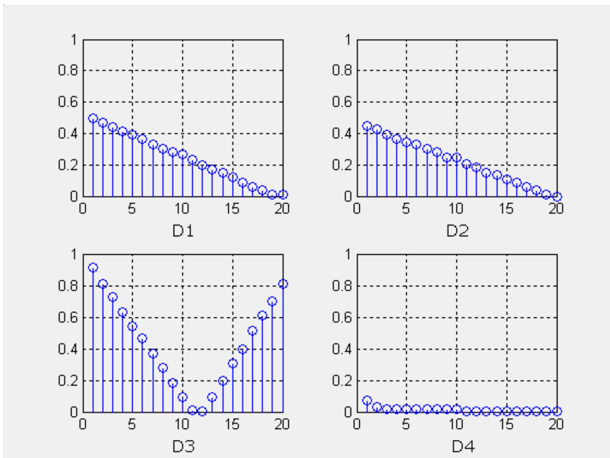
3.2. Sign Classification

There are many different methods to classify objects. Both shape and color determinate the possible ideograms that a sign can presents. Five geometric shapes are defined for Spanish signs: triangle, circle, octagon and rectangle.

In our system candidate objects to traffic sign are classified using linear SVM. SVM were introduced by Vapnik [7],[8] and they can be applied to solve either classification problems or regression.


(a)


(b)



(c)

Fig.2. (a) Red traffic sign orinal image: (b) candidate object after segmentation; (c) shape descriptors: distances to borders.

The vectors used as inputs to linear SVM are the distances from the rectangle which inscribes the object and the contours of the object. These vectors are called distance to borders (DtB) and in Fig. 2 are illustrated the four vectors for a triangular sign. In order to classify each side descriptor a SVM is used, so we have 4 SVM for each possible shape. So, an extracted object by red color feeds 4 SVM to classify the shape as a possible circle (class '1') or no circle (class '-1') and, in conclusion, four favorable votes can be obtained for each shape.

A majority voting method has been applied in order to get a classification with a threshold and so, if the total number of votes is lower than this value the analyzed object is discarded as a false alarm.

The main reason to choose a linear kernel in classification of traffic-sign is its low computational requirements with good results.

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2.3. Recognition

Once the candidate objects have been classified, the process of recognition is initiated. Recognition is implemented by SVM with a gaussian kernel because the data can not be separated by a linear function as in classification case. A solution is to map the input data into a different space using a kernel function.

The recognition stage input is a block of 31×31 pixels in gray-scale image and only those pixels belong to the inner area of the previous classified shape are computed. Thus, the objects must be normalized to these dimensions before the identification is made. The normalized dimensions are chosen as a compromise between minimum computational load and enough resolution for the recognition task.

3.4. Verification

Although false traffic-sign candidates may be discarded by their unsuitable size, shape or content of their ideogram, some of them are detected inevitably as traffic signs by our system.

Since almost signs are symmetrical about the vertical axis, as we can see in Fig. 3, the role of verification followed by our system is that a road-sign candidate is considered as authentic if the centers of gravity of the different color regions which constitute the sign are very close.

Fig. 3. Examples of different types of traffic-signs.

4. Experimental results

For automatic evaluation of the sign visibility, we propose then the measurement of the parameter V (equation 4) of traffic signs at night taken from inside the vehicle using the headlamps as light source. This is the most similar way how drivers see the signs when they approach them.

The average gray level of the image of the sign surface ($\overline{n}_g$) is then represented for different values of d.

These values are obtained automatically by the software for each sign which appears in the image set. The images were acquired with a color digital camera (Canon EOS 300D) using an objective with focal length set at f=55mm. To avoid the saturation of the image pixels and, at the same time, to decrease the influence of the movement of the car, the exposure time, numerical aperture and sensibility were set to t =1/50s, N_f=5.6 and iso1600 respectively. The selected resolution of the image was 2048×3072 pixels with a pixel size of 7.4μm^2.

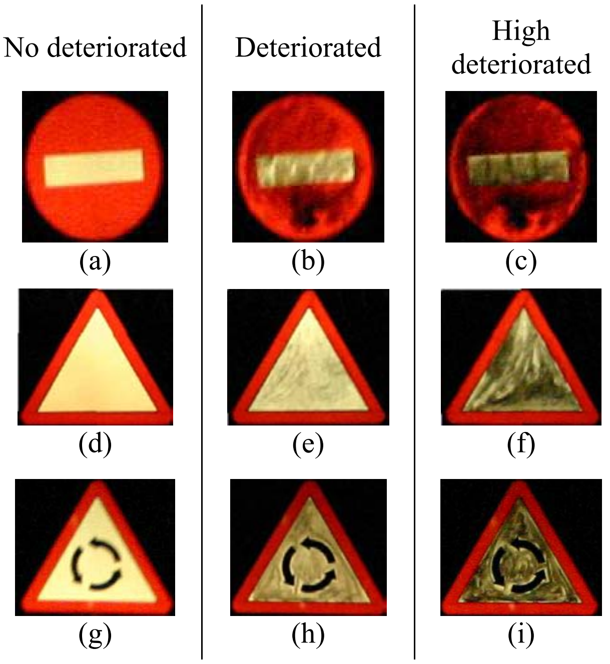

Fig. 4. Signs with different degrees of deterioration. (a),(b),(c): "Close to all vehicles" sign. (d),(e),(f): "Yield" sign. (g),(h),(i): "Round about ahead" sign.

We present here the measurements of the parameter $\overline{n}_g$ at different distances, d, for three different signs ("close to all vehicles" sign, "yield" sign, and "round about ahead" sign), where each sign presents different degrees of surface deterioration as it is shown in Fig. 4. To stand out is that even the highest deteriorated sign is detected and recognized.

In Fig. 5 we show an example of a sequence of the "yield" sign at different distances, and in Fig. 6 three graphics are illustrated where we can see the evolution of $\overline{n}_g$ as we approach the sign along the road and, therefore d decreases. The different states of deterioration mentioned above are shown in Fig. 4. In general, the influence of uncontrolled illumination of the sign (like other light sources than the headlamps, the no spatial uniformity of the light intensity emitted from the headlamps, the random positions of the sign within the headlamps light beam, the irregularities of the road, curves, brow of hills,…) introduce strong fluctuations in the value of $\overline{n}_g$. In our experiments, the measurements of signs were done along an

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approximately straight road (no curves and brow of hills), and so, the decrease of $\overline{n}_g$ at closer distances to the sign is because the sign surface move away from the maximum intensity region of the headlight beam. At far distances, where the sign surface remains in the maximum intensity region of the headlamps, there is an increase of $\overline{n}_g$ by approaching to the sign because of the increase of the illuminance at closer distance *d*. The rest of the fluctuations may by influenced by irregularities on the road. For every one of the three signs there can be clearly appreciated that $\overline{n}_g$ presents, obviously, different values depending on the sign surface deterioration.

We evaluate the visibility of the sign along the entire distance where it is seen by the motorist. Along this distance we calculate the value of the parameter V shown in the legend of the graphics in Fig. 6 and in the table 1. For the no deteriorated sign, the highest value of V is for the “yield” sign, the next highest value is for the similar “round about ahead” sign but this sign is not as reflective as the “yield” sign due to the black arrows inside. The “close to all vehicles” sign is the less reflective one, and it is even less reflective than the both deteriorated triangular signs. Thus, each sign must be analyzed separately for its visibility evaluation.

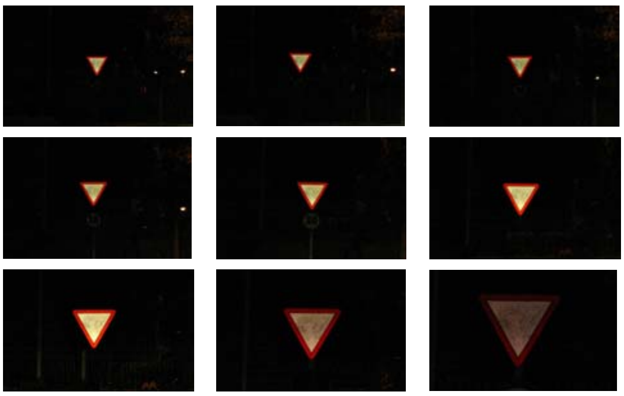
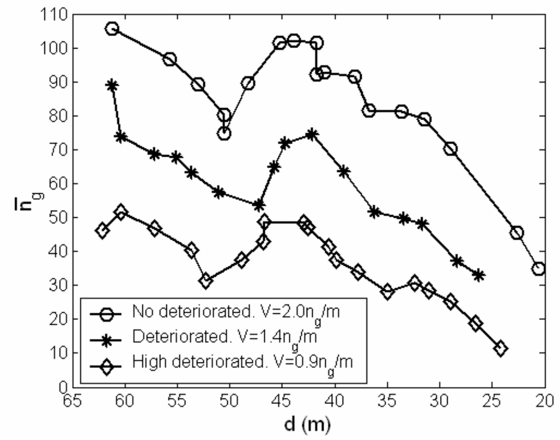


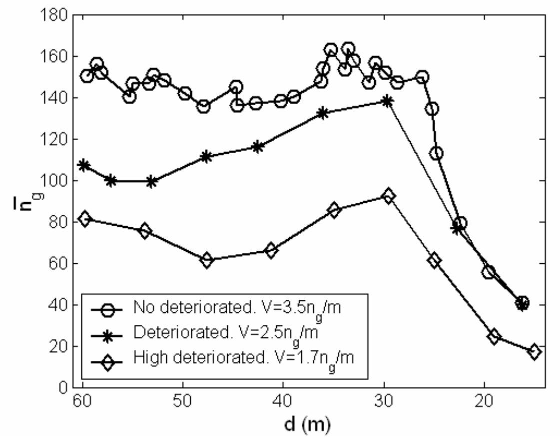
Fig. 5. Images sequence at different distances vehicle-sign.

	Close to all vehicles	Yield	Round about ahead
No deteriorated	2.0	3.5	3.4
Deteriorated	1.4	2.5	2.6
High deteriorated	0.9	1.7	1.8

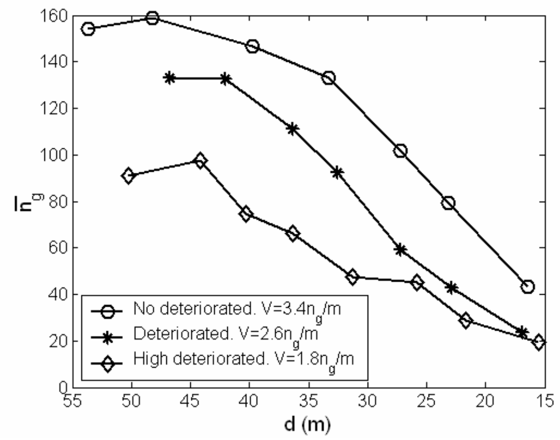
Table 1. Parameter V [average gray level/m] for different sign and degree of deteriorations.



(a)



(b)



(c)

Fig. 6. Average gray level at different distances from the signs with different degree of deterioration. (*a*) “Close to all vehicles” sign, (*b*) “yield” sign, (c) “round about ahead” sign.

5. Conclusion

We propose here an automated technique to evaluate the visibility of signs at night using just a color digital camera, a computer with the necessary software and a vehicle. For this propose we define a parameter, V, as the average value of the average gray level of the sign pixels at different sign-car distances, divided into the average distances sign-camera. These parameter indicates at once the visibility of the sign from the point of view of a motorist.

Three examples of three different signs with different degrees of deterioration show that the proposed parameter evaluates correctly the sign visibility.

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