A Statistical Approach for the Automatic Recognition of Traffic Sign Deterioration

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***Abstract*—This paper describes a software application based on statistical methods for the automatic recognition of traffic sign deterioration. The evaluation of traffic sign degradation is usually performed by devices applied on top of the road sign surface, measuring color parameters such as chromatic coordinates and the luminance factor. Moreover, the devices can only check a small fraction of the traffic sign surface at a time, requiring several acquisitions on the same traffic sign. In order to reduce the costs related to monitoring and have a periodic control of the traffic sign status, we propose a fast automatic method based on video acquisition and processing that can be easily operated in patrolling vehicles provided with a camera. A pattern detection algorithm based on color and texture features is applied to the images extracted from the acquired videos in order to detect the traffic signs ROIs, which are analyzed using a statistical approach based on the Kullback-Leibler divergence and Kolmogorov-Smirnov test. Making use of a control sample of not deteriorated traffic sign images, a comparison between the acquired and the reference images is performed. Both statistical methods have been used to compare 150 pairs of traffic signs, achieving high precision and recall, proving that the proposed approach can be a good candidate solution for automatic traffic sign deterioration analysis.**

Keywords*—*traffic sign recognition; automatic video processing; image deterioration; Kullback-Leibler divergence; Kolmogorov-Smirnov statistical test

I. Introduction

Usually, quality of the traffic sign surface concerning the reflectance and color value is evaluated remeasuring color parameters such as chromatic coordinates and the luminance factor. This requires the application of measurement devices and equipments in contact with the traffic sign surface, which cannot be performed automatically.

Moreover, these devices can only check a small fraction of the traffic sign surface at a time, requiring several acquisitions on the same traffic sign. In order to reduce the costs related to monitoring and have a periodic control of the traffic sign status, we propose a fast automatic method based on video acquisition and processing that can be easily operated in patrolling vehicles provided with a camera.

Many approaches have been proposed and are available in the literature that aim at automatically recognize the traffic sign patterns within digital images making use of well established image processing and pattern recognition techniques; see, for example, [1][2] and references therein. In [3], a method for the measurement of degradation based on retroreflectivity has been proposed, where the authors have computed the photometrical response function for each pixel in order to establish a threshold for identification of damaged traffic signs. The statistical measurement we are presenting here enables the calculation of a threshold at a more global level, measuring differences between two probability density functions.

In this paper, we present two methods to asses signal degradation by comparing degraded traffic signs with a reference sample of non-deteriorated signs. This comparison has been carried out with two methods: a divergence measure based on the Kullback-Leibler [4] distance and the Kolmogorov-Smirnov [5][6] statistical test that, to the best of our knowledge, are the only available in literature for this kind of analysis and comparison.

We have taken into account the protocols for evaluating the deterioration of traffic signs provided by italian public institutions such as the Ministry of Public Works and Transport [7], and ANAS [8], responsible for the traffic sign maintenance and control.

This paper is organized as in the following: Section II describes the image processing approach, whilst Section III reports the statistical methods analyzed and applied; Section IV provides the experimental results based on a sample of 150 traffic signs; finally, Section V summarizes the results and possible future work.

II. Image Processing

As mentioned in the introduction, we have made use of two separate image sets: one set of *non-deteriorated* traffic signs adopted as reference sample and one set of traffic signs whose degradation must be evaluated.

The reference sample has been created by manually acquiring digital images traffic signs that appeared in good conditions, and examples of degraded traffic signs have been been from roads in Turin. A patrolling vehicle with a camera has provided a series of images of traffic signs (mjpeg [9]) with the associated geospatial references stored in the EXIF [10] image format. Hence a software already developed (and tuned for high recall) [1] has recognized the traffic signs, making use of Haar cascades [11][12] for *regions of interest* (ROI) detection and a MPEG-7 [13] feature-based classifier for traffic sign identification.

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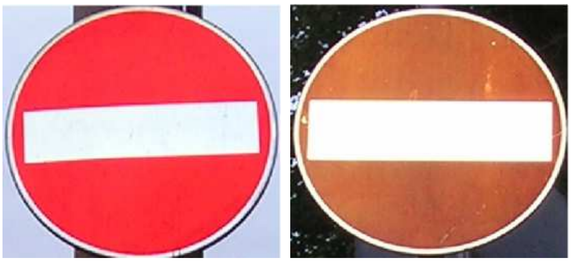

Fig. 1. Sample (left) and deteriorated (right) traffic signs

For each recognized traffic sign, the ROI has been extracted and normalized to a reference size. Finally, it has been split up into three color channels (RGB), analyzed separately in order to evaluate the pixel color level distribution.

The application has been written in C++ language and using the OpenCV [14] libraries for image manipulation.

Summarizing, the image processing flow is made up of the following five steps:

1) Image acquisition by a patrolling vehicle provided with a camera.
2) Traffic sign recognition for the acquired images
3) Image cropping for ROI selection and normalization
4) Traffic sign ROI split into RGB planes
5) Pixel color level distribution evaluation

In order to have the statistical distributions of *not deteriorated* traffic signs to be used as **control sample**, we have performed the overall processing chain to the new and unused traffic signs images acquired manually.

The information about the pixel color level distribution for both samples has then been used as input for the statistical analysis.

III. Analysis Methods

In order to evaluate the level of degradation of traffic signs, we have taken into account the color distributions of the pixels. We adopted a statistical approach for the analysis, based on the Kullback-Leibler [15] divergence and Kolmogorov-Smirnov [16] test. A comparison of the two methods has been performed in order to select the most appropriate one as a good solution for automatic recognition of road signs degradation.

The probability $\mathcal{P}(px, ch)$ that a generic pixel px belonging to a $N \times M$ image has a given color level ℓ (with $\ell = 0, ..., 255$) in a specific color channel ch (where $ch = R, G, B$) is given by:

$$\mathcal{P}(px, ch) = \frac{(n_\ell)_{ch}}{(N \times M)_{ch}} \tag{1}$$

where $(n_\ell)_{ch}$ is the number of pixels having color level ℓ.

In order to compute the probability function of the **control sample**, an average value of $\mathcal{P}$ is evaluated using all the images representing a specific traffic sign. These values are compared with the probability function computed for each actual traffic sign image acquired.

Here, we have compared the probability functions associated to the same color channel of the traffic signs acquired as mentioned above and the control sample.

A. Kullback-Leibler divergence

The Kullback-Leibler divergence $\mathcal{D}_{kl}$, associated with two probability distributions $f(x)$ and $g(x)$, is defined as follows:

$$\mathcal{D}_{kl}(f \parallel g) = \int f(x) \log \frac{f(x)}{g(x)} dx \tag{2}$$

where x is a random continuous variable.

In our analysis, the random variable x is associated to the digital color levels, moving from continuous to discrete, and $f(x), g(x)$ are the probability distributions associated to the same color channel of the two images to be compared (the sample and deteriorated sign). Moreover, the equation (2) is not symmetric.

In order to use discrete variables and symmetric functions, the Kullback-Leibler divergence definition given in (2) can be rewritten in a symmetric form $\mathcal{S}_{kl}$ as:

$$\begin{aligned} \mathcal{S}_{kl}(f \parallel g) &= \mathcal{S}_{kl}(g \parallel f) = \\ &= \mathcal{D}_{kl}(f \parallel g) + \mathcal{D}_{kl}(g \parallel f) = \\ &= \sum_{x=0}^{N} \left[(f(x) - g(x)) \log \frac{f(x)}{g(x)} \right]. \end{aligned} \tag{3}$$

In order to remove the singularity for $g(x) = 0$, every $g(x)$ is added a small value ϵ chosen as:

$$\epsilon = \frac{gmax}{N} = \frac{1}{256} \tag{4}$$

where N is the total number of color levels. Using the transformation $g'(x) = g(x) + \epsilon$, equation (3) becomes:

$$\mathcal{S}_{kl}(f \parallel g') = \sum_{x=0}^{N} \left[(f(x) - g'(x)) \log \frac{f(x)}{g'(x)} \right] \tag{5}$$

$\mathcal{S}_{kl}$ is calculated for each probability distribution pair related to the same color channel. The three evaluated divergences are summed up to a total divergence $\mathcal{S}_{kl}^{tot}$. If the overall amount exceeds a threshold value T, the traffic sign is declared *deteriorated* ($\mathcal{S}_{kl}^{tot} > T$).

B. Kolmogorov-Smirnov test

The other method used is the Kolmogorov-Smirnov test for two samples, which compares two *cumulative distribution functions*, related to two data sets, in order to estimate if they belong to the same distribution which can be unknown.

We have experienced that applying the test to all the pixels of the image, we overestimate the degree of freedom of the test because many pixels are correlated to their neighbors. Pixel correlation is evaluated to the images converted to greyscale values and applying the following algorithm:

$$\begin{aligned} g(x, y) &= w(x, y) \cdot f(x, y) = \\ &= \sum_{s=-a}^{a} \sum_{t=-b}^{b} w(s, t) \cdot f(x + s, y + t) \end{aligned} \tag{6}$$

where $f(x, y)$ is the greyscale value of the pixel (x, y), $w(x, y)$ is the weight of the $m \times n$ correlation mask, $g(x, y)$ is the correlation level, $a = \frac{m-1}{2}$ and $b = \frac{n-1}{2}$

If $g(x,y)$ is $null$ there is no variations between pixel at (x,y) and its neighbors.

In order to reduce number of correlated pixels, we have applied the *Canny* [17] edge detector and considered solely filtered pixels. Canny edge detector provides greyscale conversion, noise reduction, correlation evaluation, minimal gradient suppression, hysteresis threshold.

The two cumulative distribution functions for each image have been calculated using only the pixels belonging to the edges, separately for each color channel:

$$\mathcal{F}_{ch} = \{\mathcal{F}_c, c = 0, ..., 255\}_{ch} \tag{7}$$
$$\mathcal{G}_{ch} = \{\mathcal{G}_c, c = 0, ..., 255\}_{ch} \tag{8}$$
$$\mathcal{F}_c = \sum_{\ell=0}^{c} h_\ell \tag{9}$$
$$\mathcal{G}c = \sum_{\ell=0}^{c} h_\ell \tag{10}$$

where h_ℓ and h'_ℓ are the color level frequencies. Given $\mathcal{F}_c h$ and $\mathcal{G}_c h$, the maximum distance can then be calculated:

$$\mathcal{D}_{ks} = max \mid \mathcal{F}_{ch}\mathcal{G}_{ch} \mid \tag{11}$$

The output of (11) can be compared to a threshold value λ, thus determining whether the two distributions are significantly different. Giving $\mathcal{J}$ as the following value:

$$\mathcal{J} = \frac{NcNd}{Nc + Nd} \tag{12}$$

where Nc is the total number of pixel in a good image channel and Nd is the total number of pixel in a deteriorated image channel, we can compare the equation (11) to:

$$\mathcal{D}_{ks} \geq \frac{\lambda}{\sqrt{\mathcal{J}}} \tag{13}$$

If the inequality (13) is not satisfied, we can say that the distributions are significantly different with a level of significance associated to the threshold level λ. It means that the evaluated traffic sign is deteriorated and should be replaced.

IV. Experimental Results

Both methods described in the paper, the Kullback-Leibler divergence and the Kolmogorov-Smirnov test, have been applied on 150 traffic signs pairs (the sample and the deteriorated). According to the analysis procedure described in Section III-A, the threshold T has been chosen evaluating the distribution of $\mathcal{S}_{kl}^{tot}$ corresponding to the 150 traffic signs pairs. Fig. 2 shows the Gaussian fit to the data, whose mean μ and standard deviation σ are calculated. The threshold value has been chosen as $T = \mu - \sigma = 2.5$. We obtained a χ^2 value equal to 4.618 with 11 degrees of freedom and the Gaussian distribution hypothesis can be accepted with a significance level of $\alpha = 0.05$. We also tried to fit the data with a Poisson distribution, which gives a $\chi^2 = 3.201$ with 12 degrees of freedom ($\alpha = 0.05$) and the obtained threshold $T = 2.8$ does not change significantly.

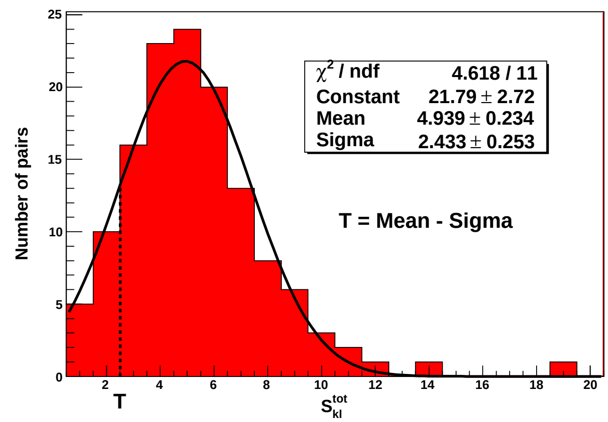

Fig. 2. S_{kl}^{tot} with fit results using a Gaussian distribution and the chosen threshold T.

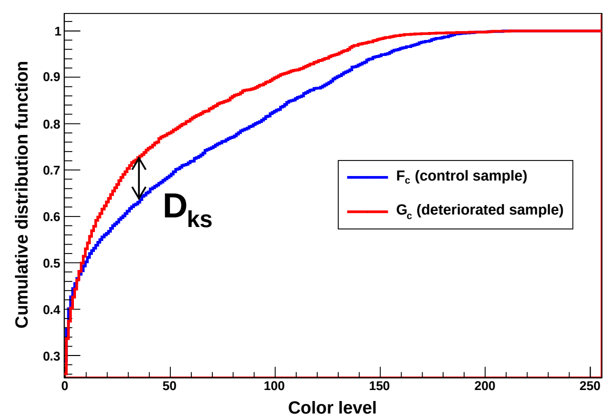

Fig. 3. Cumulative distribution functions $\mathcal{F}_{ch}$ and $\mathcal{G}_{ch}$ for the control sample (blue) and deteriorated sample (red) with the chosen $\mathcal{D}_{ks}$ after applying the edge filter

According to the analysis method discussed in Section III-A, Fig. 3 shows the cumulative distribution functions $\mathcal{F}_{ch}$ and $\mathcal{G}_{ch}$ for the traffic sign samples with the application of the edge filter where the selected value of $\mathcal{D}_{ks}$ is also displayed.

Precision, recall and accuracy are evaluated according to the following equations:

$$precision = \frac{tp}{tp + fp} \tag{14}$$
$$recall = \frac{tp}{tp + fn} \tag{15}$$
$$accuracy = \frac{tp + tn}{tp + tn + fp + fn} \tag{16}$$

where tp are the true positive, tn are the true negative, fp are the false positive and fn are the false negative values.

The calculated values are reported in Table I. It shows that both methods have good accuracy, precision and recall.

TABLE I. RESULTS FOR A SAMPLE SET OF 150 TRAFFIC SIGN PAIRS

Method	Accuracy	Precision	Recall
Kullback-Leibler	0.80	0.88	0.79
Kolmogorov-Smirnov	0.88	0.93	0.89

The Kolmogorov-Smirnov method appears to give a better performance, with 89% recall and 93% precision.

V. CONCLUSION AND FUTURE WORK

Values in Table I show that both Kullback-Leibler divergence and Kolmogorov-Smirnov test achieve high accuracy, precision and recall parameters, so both methods can, in principle, be used.

However, Kolmogorov-Smirnov test results in the highest values of statistical parameters; indeed the Kullback-Leibler divergence gives only a measure of the distance between two distributions, and cannot capture the statistics of the samples as done by the Kolmogorov-Smirnov test.

The method presented here could be, for instance, applied to automatic monitoring of traffic sign deterioration: a camera could be installed onto public transportation vehicles patrolling the roads and acquiring the digital images [1] that then could be processed. A traffic signs catalogue could thus be generated enabling to determine in advance (before their scheduled expiring time) the traffic signs to be replaced.

A possible improvement of the proposed approach that the authors would like to implement as future work, is the use of HSV (Hue Saturation Value) color space instead of RGB, because the distance between two colors in HSV dimensions is closer to the human eye color perception. Hence, the presented statistical methods should result in a better evaluation of color deterioration. Since HSV has a clear separation between luminance and colors, it is more suitable to appraise the color variations, even in case of large changes of luminance. Nevertheless, it should be considered that the hue (H) component which holds color information in HSV color space depends on distance, weather conditions, and age of traffic sign [18].

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