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# Road signs detection in color images by statistical approach

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**Abstract**—In this paper we present a statistical approach for the detection of road signs present in an image by using only color related information.

**IndexTerms**—Detection, road signs, directional T<sup>2</sup> Hotelling, RGB, HSV

## I. INTRODUCTION

Artificial vision used for the detection and recognition of objects is increasingly used in the design of intelligent and autonomous vehicles which are able to recognize their environment. In this context, the detection and recognition of road signs is an essential aspect helping to reduce the number of road accidents.

Two main categories of approaches are proposed for the detection of road signs: approaches exploiting color information and approaches using form recognition.

Detection approaches based on form recognition use the fact that the form of road signs is standardized (triangular, circular, rectangular, etc.). These approaches are based on recent advances in pattern recognition techniques [6], but they also have a number of drawbacks among which we can mention: the perspective effect in the image can distort objects thus making them difficult to recognize; objects whose shape is close to that of the road signs may induce some ambiguity in the recognition. In [10], the extension of the radially symmetrical transformation [11] is used to detect the points of interest. The authors propose a detector of regular polygons, and use it to detect road signs. The overall approach is similar to the generalized Hough transform [12]. In [13] and [14], the detection is performed by computing the correlation between a sample image and a distance map derived from the original image.

Detection approaches exploiting color information in different color spaces, allow the identification of the class of the panel (i.e., danger - characteristic color: red, obligation - characteristic color: blue, in work - characteristic color: yellow, directional signs - characteristic color: green), but also have a high sensitivity to brightness changes caused by daily, weather or seasonal variations. In fact, the color fades over time due to sun exposure, and visibility is affected by weather conditions

(i.e., rain, snow, etc.). In addition, the light characterizing different daily moments has a direct impact on the information color (i.e., dark, sun, clouds, etc.).

In [5], a color segmentation technique was used to extract an object from the background of the image and the “Mean-shift” algorithm permits to distinguish between each object in the image. In [1], segmentation was performed in different color spaces (RGB, HSV, YCbCr, CIElab ...) by thresholding the image and threshold values were obtained by taking into account different weather and light during the day. Similarly, in [2], thresholds were used to determine the class of a pixel in the image: pixel red, blue, green, white or black. Binarization technique based on Otsu algorithm [4], provides thresholds in HSV color space. In [3], a technique of color constancy has been used in order to reduce the effect of the brightness when doing segmentation. Indeed, color consistency can represent the image in a space where the recognition of the true color of a pixel is not affected by light (thus certain color stability is obtained).

Recently, some hybrid approaches (jointly exploiting the information provided by the color and shape) have been emerged. Thus, in [6] and [7], the color is used to reduce the searching area of the panels on the image and to extract the suitable forms.

In this paper, we propose a new technique for detecting road signs present in an image based on the directional T<sup>2</sup> test of Hotelling which is largely used in SPC (Statistical Process Control) field in order to detect changes in the mean of a multivariate process.

The paper is structured as follows: we present in section II some theoretical concepts related to the T<sup>2</sup> Hotelling test; in section III we describe the principle of our method; in section IV we present an application of the new proposed methodology and, finally, in Section V we present some conclusions and perspectives.

## II. STATISTICAL DETECTION OF MEAN SHIFTS

Statistically, the detection of a mean shift in a p-variate process is formalized as a hypothesis test:

$$\begin{aligned} H_0: \boldsymbol{\mu} &= \boldsymbol{\mu}_0 \\ H_1: \boldsymbol{\mu} &\neq \boldsymbol{\mu}_0 \end{aligned} \quad (1)$$

$$\begin{aligned} H_0: \boldsymbol{\mu} &= \mathbf{0} \\ H_1: (\boldsymbol{\mu} = \delta \mathbf{d}_1) \cup (\boldsymbol{\mu} = \delta \mathbf{d}_2) \cdots \cup (\boldsymbol{\mu} = \delta \mathbf{d}_r) \end{aligned} \quad (9)$$

where:  $\boldsymbol{\mu}$  is the mean vector;  $\boldsymbol{\mu}_0$  is the target vector.

Without reducing the generality of the problem, we can consider that  $\boldsymbol{\mu}_0 = \mathbf{0}$ . If the specific direction of the mean shift is known, the hypothesis test in Eq.1 can be written:

$$\begin{aligned} H_0: \boldsymbol{\mu} &= \mathbf{0} \\ H_1: \boldsymbol{\mu} &= \delta \mathbf{d} \end{aligned} \quad (2)$$

where:  $\mathbf{d}$  is the direction vector (known) and  $\delta$  is the shift amplitude (scalar unknown).

In this case, the test statistic is derived from the likelihood ratio [8]:

$$S_{\text{test}} = \frac{(\mathbf{d}^T \boldsymbol{\Sigma}^{-1} \bar{\mathbf{X}})^2}{\mathbf{d}^T \boldsymbol{\Sigma}^{-1} \mathbf{d}} \quad (3)$$

where:  $\boldsymbol{\Sigma}$  is the variance-covariance matrix,  $^T$  designs the transposition operator and  $\bar{\mathbf{X}}$  is the vector of means at each sampling instance.

The null hypothesis in Eq.2 is rejected if:

$$S_{\text{test}} > \chi_{\alpha, p}^2 \quad (4)$$

where:  $\chi_{\alpha, p}^2$  is the quantile of order  $\alpha$  of the chi-square distribution with  $p$  degrees of freedom.

An equivalent statistic test of those presented in Eq.3 is obtained by choosing an unitary norm direction vector  $\mathbf{d}$  (i.e.  $\|\mathbf{d}\|_{\boldsymbol{\Sigma}} = (\mathbf{d}^T \boldsymbol{\Sigma}^{-1} \mathbf{d})^{\frac{1}{2}} = 1$ ):

$$S_{\text{test}} = \mathbf{d}^T \boldsymbol{\Sigma}^{-1} \bar{\mathbf{X}} \quad (5)$$

$$|S_{\text{test}}| > \Phi^{-1} \left( 1 - \frac{\alpha}{2} \right) \quad (6)$$

Thus, the null hypothesis in Eq.2 is rejected if:

where:  $\Phi(\cdot)$  is the cumulative distribution function of the standard normal distribution and  $\alpha$  is the type I error.

If the direction of the mean shift is not known in advance,

$$S_{\text{test}} = \max_{\|\mathbf{d}\|_{\boldsymbol{\Sigma}}=1} \{\mathbf{d}^T \boldsymbol{\Sigma}^{-1} \bar{\mathbf{X}}\} \quad (7)$$

then the test statistic suggested by [9] is the generalized likelihood ratio:

It is easy to see that the test statistic of the generalized likelihood ratio in Eq. 7 reaches its maximum when  $\mathbf{d} =$

$$S_{\text{test}} = \bar{\mathbf{X}}^T \boldsymbol{\Sigma}^{-1} \bar{\mathbf{X}} > \chi_{\alpha, p}^2 \quad (8)$$

$\bar{\mathbf{X}}/\|\bar{\mathbf{X}}\|_{\boldsymbol{\Sigma}}$  and, consequently, the test performed is nothing other than the Hotelling  $T^2$  test which rejects the null hypothesis if:

A special situation is to test several possible directions for the mean shift:

where:  $\mathbf{d}_1, \mathbf{d}_2, \dots, \mathbf{d}_r$  are the direction vectors of the known mean changes.

The rejection of the null hypothesis is obtained if the following statistics:

$$S_{\text{test}} = \max_{i=1,2,\dots,r} \left\{ \frac{(\mathbf{d}_i^T \boldsymbol{\Sigma}^{-1} \bar{\mathbf{X}})^2}{\mathbf{d}_i^T \boldsymbol{\Sigma}^{-1} \mathbf{d}_i} \right\} \quad (10)$$

exceeds a certain critical value.

Another commonly used test statistic in this case is:

$$S_{\text{test}} = \max_{i=1,2,\dots,r} \{|\mathbf{d}_i^T \boldsymbol{\Sigma}^{-1} \bar{\mathbf{X}}|\} \quad (11)$$

If the null hypothesis is rejected, one can use the following statistics to estimate the direction of the mean shift:

$$S_{\text{test}} = \arg \max_{\mathbf{d}_i = \mathbf{d}_1, \mathbf{d}_2, \dots, \mathbf{d}_r} \left\{ \frac{(\mathbf{d}_i^T \boldsymbol{\Sigma}^{-1} \bar{\mathbf{X}})^2}{\mathbf{d}_i^T \boldsymbol{\Sigma}^{-1} \mathbf{d}_i} \right\} \quad (12)$$

In the case of estimated parameters, the test statistic for detecting mean shifts given in Eq. 8 becomes:

$$S_{\text{test}} = (\bar{\mathbf{X}} - \hat{\boldsymbol{\mu}}_0)^T \hat{\boldsymbol{\Sigma}}^{-1} (\bar{\mathbf{X}} - \hat{\boldsymbol{\mu}}_0) \quad (13)$$

where:  $\hat{\boldsymbol{\mu}}_0$  is the estimate of the mean vector;  $\hat{\boldsymbol{\Sigma}}$  is the estimate of the variance-covariance matrix.

Thus, a mean shift is detected if:

$$S_{\text{test}} > \frac{p(m-1)(n-1)}{mn-m-p+1} F_{\alpha, p, mn-m-p+1} \quad (14)$$

where:  $F_{\alpha, p, mn-m-p+1}$  is the  $\alpha$  order quantile of the Fisher distribution with  $p$  and  $mn-m-p+1$  degrees of freedom;  $m$  is the number of samples of size  $n$  used in order to obtain the estimates of  $\boldsymbol{\mu}_0$  and  $\boldsymbol{\Sigma}$ .

If the sample size is unitary ( $n=1$ ), one can detect a mean shift if:

$$S_{\text{test}} > \frac{(m-1)^2}{m} B_{\alpha, \frac{p}{2}, \frac{m-p-1}{2}} \quad (15)$$

where:  $B_{\alpha, \frac{p}{2}, \frac{m-p-1}{2}}$  is the  $\alpha$  order quantile of the beta distribution with  $\frac{p}{2}$  and  $\frac{m-p-1}{2}$  degrees of freedom.

### III. PROPOSED DETECTION APPROACH

Let  $\mathbf{X}$  be the matrix of pixels of an image of size  $n \times m$  (see Fig. 1). Hereafter, we will adopt the following notations:  $\mathbf{x}_i$  ( $i =$

$1, \dots, n$ ) is the  $i$  row of the image (a vector of size  $1 \times m$ );  $\mathbf{x}_{\cdot j}$  ( $j = 1, \dots, m$ ) is the  $j$  column of the image (a vector of size  $n \times 1$ );  $\mathbf{x}_{ij} = \{x_{ij}^r, x_{ij}^g, x_{ij}^b\}^T$  represents the pixel located at the intersection of the row  $i$  and column  $j$  of the image (where  $x_{ij}^r, x_{ij}^g, x_{ij}^b$  are the red, green and blue components of the  $x_{ij}$  pixel);  $\mathbf{x}_i^k$  ( $k \in \{r, g, b\}$ ) represents the red, green or blue components of the  $i$  row in the image;  $\mathbf{x}_j^k$  ( $k \in \{r, v, b\}$ ) represents the red,

$$\hat{\boldsymbol{\mu}}_i = \hat{\boldsymbol{\mu}}_i^{(t)} \text{ and } \hat{\boldsymbol{\Sigma}}_i = \hat{\boldsymbol{\Sigma}}_i^{(t)} \quad (19)$$

green or blue components of the  $j$  column in the image.

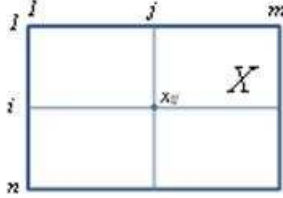


Fig. 1. Matrix representation of an image.

The algorithm we propose consists of two steps: the parameters estimation and the detection of the road sign.

#### A. – Estimation of the parameters

The parameters (mean vector and covariance matrix) of each line of the image are estimated by an iterative approach. Iteration is defined by the sequence of steps 1 and 2 described below:

$$\hat{\boldsymbol{\mu}}_i^{(1)} = \{\hat{\boldsymbol{\mu}}_i^{r(1)}, \hat{\boldsymbol{\mu}}_i^{v(1)}, \hat{\boldsymbol{\mu}}_i^{b(1)}\} \quad (16)$$

**Step 1:** For each row we estimate the mean vector and the variance-covariance matrix of the three RGB components.

where:  $\hat{\boldsymbol{\mu}}_i^{k(1)} = \bar{\mathbf{x}}_i^k$  is represents the average, at iteration 1,

$$\hat{\boldsymbol{\Sigma}}_i^{(1)} = \begin{bmatrix} \hat{\sigma}_r^{2(1)} & \hat{\sigma}_{rv}^{(1)} & \hat{\sigma}_{rb}^{(1)} \\ \hat{\sigma}_{vr}^{(1)} & \hat{\sigma}_v^{2(1)} & \hat{\sigma}_{vb}^{(1)} \\ \hat{\sigma}_{br}^{(1)} & \hat{\sigma}_{bv}^{(1)} & \hat{\sigma}_b^{2(1)} \end{bmatrix} \quad (17)$$

of the component  $k \in \{r, g, b\}$  for the line  $i$ .

where:  $\hat{\sigma}_k^{2(1)} = \frac{1}{m-1} \sum_{j=1}^m (x_{ij}^k - \hat{\mu}_i^{k(1)})^2$  represents the variance (calculated at iteration 1) of the component  $k \in \{r, g, b\}$  for the line  $i$ ;  $\hat{\sigma}_{kl}^{(1)} = \frac{1}{m} \sum_{j=1}^m (x_{ij}^k - \hat{\mu}_i^{k(1)})(x_{ij}^l - \hat{\mu}_i^{l(1)})$  is the covariance between the components  $k$  and  $l$  ( $k, l \in \{r, v, b\}$  and  $k \neq l$ ).

**Step 2:** for each row  $i$  the Hotelling  $T^2$  statistic is calculated

$$T_{ij}^2 = (\mathbf{x}_{ij} - \hat{\boldsymbol{\mu}}_i^{(1)})^T \hat{\boldsymbol{\Sigma}}_i^{(1)-1} (\mathbf{x}_{ij} - \hat{\boldsymbol{\mu}}_i^{(1)}) \quad (18)$$

as follows:

Observations exceeding the threshold  $B_{\alpha, \frac{p}{2}, \frac{m-p-1}{2}}$  (see Eq. 15) are eliminated.

During the next iteration (iteration 2), the mean vector  $\hat{\boldsymbol{\mu}}_i^{(2)}$  and the variance-covariance matrix  $\hat{\boldsymbol{\Sigma}}_i^{(2)}$  of each line are recalculated and the new statistics  $T_{ij}^2$  compared again to the critical threshold.

Iterations are renewed until no observation exceeds the critical threshold. Let's  $t$  be this iteration, then the validated estimators of the mean and the variance-covariance matrix used in the detection phase are:

#### B. Detection of the road signs

At this step, we use a directional test as described in Eq. 9, using privileged directions corresponding to red ( $d_r$ ), green ( $d_g$ ), blue ( $d_b$ ) and yellow ( $d_y$ ).

In the RGB space these four directions are characterized by the vectors:

$$\begin{cases} d_r = \{255, 0, 0\} \\ d_g = \{0, 255, 0\} \\ d_b = \{0, 0, 255\} \end{cases} \quad (20)$$

Due to various constraints related to the acquisition of the image (brightness, meteorological conditions, etc.), the real values of the four colors of interest for us in the image are slightly different from the theoretical directions given in Eq. 20. So, in order to determine the corresponding directions to these four colors while taking into account the effect of light, we chose to work in HSV space (Hue, Saturation and Value) that separates chrominance from luminance. For example, in this space the direction vector of red color is given by:

$$d_r(\text{HSV}) = \{0, 0.7, v\} \quad (21)$$

We deduced the value of "v" as an average brightness calculated from the histogram of the brightness of the entire image. Then, the final direction vector in the RGB space is obtained by the conversion of the direction vector from the HSV space to the RGB space.

## IV. EXAMPLE OF APPLICATION

We were not able to compare the performances of our method with other methods proposed in the literature because there is not a common base of images in the research area of road sign detection approaches. Therefore, we present in this paragraph just an illustration of the detection efficiency of the methodology we propose.

In Fig.2.a a color image of  $200 \times 200$  pixels containing a road sign is given. In Fig. 2.b we give the results of our detection methodology.

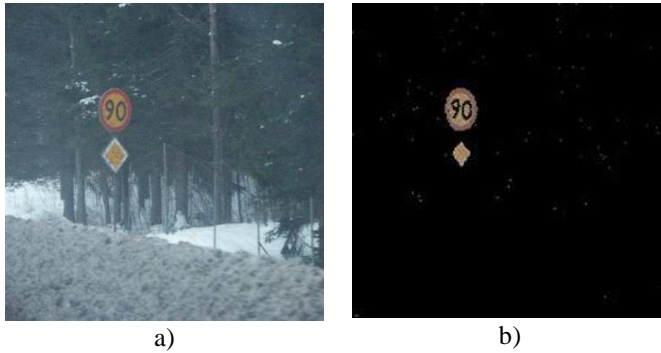


Fig. 2. Original image (a) and the detection of the road sign (b).

Each time the control limit of the directional  $T^2$  control chart was exceeded, we kept the original color of the respective pixel, and otherwise the pixel color was set to black.

One can see that our methodology is able to identify easily the presence of the road sign on the image and to delimit precisely its real shape.

In Fig.3 we give another example of road sign detection in very different brightness conditions when compared with the situation presented in Fig.2.

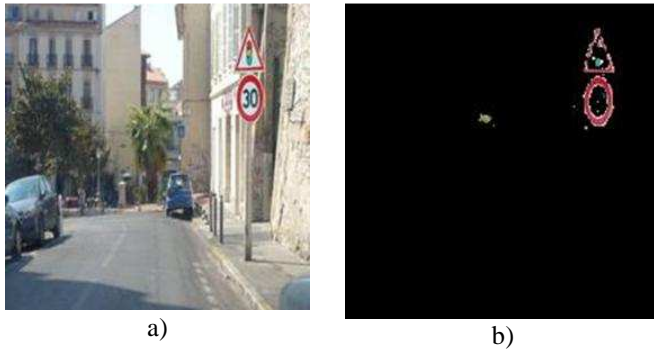


Fig. 3. Original image (a) and the detection of the road sign (b).

As one can observe, the road sign is well detected but there is also present in the image a green spot which is belonging to the tree appearing in the center of the image. Residual objects like this could be easily eliminated by the road sign recognition algorithm which should be used in conjunction with the detection algorithm we proposed in order to identify precisely the type of the road sign detected.

## V. CONCLUSION

In this article we discussed the problem of detecting road signs in an image, providing a statistical approach able to detect different panels in different weather and light stress. The detection of the road sign is realized through a directional statistical test (Hotelling's  $T^2$  test) using only the color information of pixels.

This detection approach could represent a first step in the frame of more complex road sign identification algorithm based on statistical tools.

One further extension of the proposed detection algorithm could be the detection of road signs in a movie sequence.

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