Road signs shapes detection based on Sobel phase analysis

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Abstract—This paper presents a method for triangular and rectangular shapes detection in a road sign recognition system based on a three step algorithm: color segmentation, shape detection and neural network classification. The shape detector is based on the evaluation of the Sobel edges and Hough images in a region of interest detected by the color-based stage. During the tests performed the shape detector shows its robustness to rotation, occlusion and deformation, despite a 10% increasing of total computational times compared with that requested by the pattern matching.

I. INTRODUCTION

Since road accidents are mainly caused by human errors, achieving robust traffic signs recognition systems is an important issue to ensure safety on the road. Different lighting conditions, paint degradation, dirt, shadows, partial occlusion, rotation, deformation are critical factors for the reliability of an automatic sign recognition system. The main task of this paper is to propose a simple shape detector independent from geometric distortion i.e. rotation, partial occlusion, deformation, translation. Many approaches are presented in literature for shape detection: [1], [2], [3] show that pattern matching is a robust and fast method; in [4] Hough transformation based on radial symmetry is used to detect speed signs. Genetic algorithms, used in [5], [6], [7], [8], allow accurate results in shapes detection, but their execution requires computational times unsuitable for real-time applications. Other methods ([9], [10], [11]) are based on the use of supervised learning methods for classification, like SVM. Some methods recognize only a specific shape: [12], [13], [14] present a triangular shapes detector; in [4], [1] only circular shapes are detected; the algorithm presented in [15] allows triangles, rectangles and octagons detection, through the use of a fast radial symmetry and the shape center detection. In [16] has been presented a vertical traffic sign recognition system based on a three-step algorithm: color segmentation, shape recognition and neural network classification to detect and classify almost all Italian traffic signs. The shape detection method described was sensible to translation and rotation of signs. To address this problem the proposed approach detects edges on images, correlating them with their gradient distribution: the shape of a placed object depends intact on the edges and on their features i.e. position and mutual orientation.

The paper is organized as follows: section II briefly explains the processing for edges detection; section III presents a comparative analysis about the distribution of Sobel phases for triangular, rectangular, circular and invalid shapes. Section IV describes the algorithm to identify triangular and rectangular shapes, in order to detect the region of interest for the neural network. Section V provides some experimental results and finally, in section VI conclusions are drawn.

II. EDGES DETECTION

A conversion from RGB to grey scale images is performed to detect edges: each region limited by a bounding box is cropped from the color image (figure 1a) and converted to a grey scale crop (figure 1b). Since the RGB to grey conversion causes information loss due to the passage from a vector field (color image) to a scalar field (grey image), in order to increase the signal to noise ratio, the predominant color component, according to the primary color of each bounding box detected, is extracted from original crop and pointed out in that grey. The following formulas are used for this conversion.

\[
\text{Red} : \min \left( \frac{r}{\max(g, b)} \right) \ast 85, 255 \\
\text{Blue} : \min \left( \frac{b}{\max(r, g)} \right) \ast 85, 255 \\
\text{Yellow} : \min \left( \frac{\min(r, g)}{b} \right) \ast 85, 255
\]

The factor 85 has been experimentally computed to best enhance the primary color contribution.

In order to enhance edges, Sobel operator with a 5\times 5 mask is applied for each grey scale crop, obtaining images about the Sobel norm (figure 1b) and the Sobel phase (figure 1c) intended as \( \arctg(G_y/G_x) \).

III. ANALYSIS OF THE SOBEL PHASE DISTRIBUTION

Using images obtained by Sobel filtering, analysis about the phase distribution of Sobel edges is performed to detect distinctive features for each shape. This step focus on the...
study of the most frequently edge gradient for each region of interest detected, to decide if the placed object has a road sign compatible shape and which one is. The main purpose of this step is the study of the peaks in the sobel edges phase distribution, regardless the sign of the transition described by each edges. Since opposite transitions cause in the sobel phases image angles at a distance equal to $\pi$, statical results representend in the range $(-\pi, \pi)$ are mapped to the range $(0, \pi)$, because at this step we are interested in the study of the edge gradient most frequent directions. Figure 2 shows, for each considered shape, the ideal trend of its phase distribution; according to the shape of interest the distinctive features are:

- (a) 3 peaks placed at a distance equal to $\frac{\pi}{3}$ for triangles;
- (b) 2 peaks set at a distance equal to $\frac{\pi}{2}$ for rectangles;
- (c) histogram with all equal values for each considered angle in case of circles.

Some examples relative to phase distribution of real signs are reported in figure 3: empirical results show that the phase distribution of danger signs (figures 3a, 3b) and indication signs (figures 3c, 3d) substantially follow a common trend similar to the expected ones shown respectively in figure 2a and figure 2b. Otherwise the histograms of figures 3e, 3f show as the phase distribution of two different types of circular signs are different from each other and far from the ideal trend of figure 2a. This is due by the symbols drawn on the sign and by the elements placed on the background that introduce significant oscillations on the phase histogram involving a trend different from the ideal constant one. The same noisy elements affect also the phase distribution of triangular and rectangular shapes, but in these cases the distinctive peaks of the phase histogram are greater than the oscillations introduced by the noisy components.

Statistical analysis on the real signs is performed in order to evaluate, as distinctive feature, the real gap among peaks in the sobel phases distribution according to the shape delimited by the bounding box. The distance between two peaks is estimated as the minimum of circular distance, calculated in clockwise and anticlockwise directions:

$$\min \left( \text{abs}(v_1 - v_2), \text{range} - \text{abs}(v_1 - v_2) \right)$$

Since the minimum circular distance between two peaks in the range $(0, \pi)$ could vary between $0$ and $\frac{\pi}{2}$, for the analysis of the real gap we consider discrete intervals of the range $(0, \frac{\pi}{2})$, i.e. the x-axis is split in 23 discrete intervals of width equal to $\frac{\pi}{472}$ (4 degrees). On figure 4 are shown the bar charts of the obtained results: x-axis represent all possible gaps among the phase distribution peaks, centering the peak on each discrete range considered; while the ordinate shows in logarithmic scale the number of pixel having that phase or its supplementary.

According to the expectations, as shown in figure 4, bounding boxes with triangular shape are concentrated in a neighborhood of the ideal peak gap value i.e. 60 degrees; for the selection of the largest number of regions looking for triangles, we consider as possible candidates all bounding boxes having a peak gap in a range on the left and on the right of ideal peak gap value. The range value has been
IV. TRIANGLES AND RECTANGLES DETECTION

A. Triangles

All triangular road signs (danger, work in progress and yield) have a thick red border that generates two concentric triangles (figure 5): the biggest coincide with the edges that separate the sign from the background, otherwise, the smallest delimits the inner area (white or yellow) where symbols are painted.

The aim of this step is to verify that candidates selected by the peak gap analysis of the Sobel phase distribution match a triangular shape, and then crop the inner area that frames information for the classification stage. We are also interested in the detection of the edges separating the sign from the background because they could contribute to the detection of the inner triangle when the bounds of the inner area are not well contrasted (figure 6).

To reach this goal we detect in the candidate crops all lines that could generate a two concentric triangles compatible with the presence of a triangular road sign: the mutual position of this lines will allow to verify the presence of a triangle, defining its orientation and validating the relative bounding box. A valid bounding box could be then set with more precision, in order to crop only the inner part of the sign to be processed by the neural network. To discriminate between the inner and the outer edge of the red strip we need to consider the sense of the gradient. The searching of these edges is performed independently from their position. To detect the six lines that generate the six sides relative to the concentric triangles, we consider six different membership categories for the pixels of the image (seven counting the pixels that do not belong to any categories), according to the value of the Sobel phase (i.e. direction and sense of the gradient). This categories are associated to the six principal directions of the lines to be detected: three for the outer triangle and three for the inner one. The algorithm calculates six ideal angles, compatible with the presence of two triangular concentric shapes; these angles are fixed at multiple distances of $\frac{\pi}{3}$, starting from the first peak angle detected in the phase distribution. We consider a neighborhood of $\frac{\pi}{3}$ centred on each angle, in order to recover the domain $(0, 2\pi)$; every range will define a different category. According to the value of the Sobel phase, every pixel is classify as member of a category. After the categorization we obtain a grey scale image, where pixels could assumed only seven values (six categories and the value 0 to distinguish all points to be discriminated). An example of categorization is shown on figure 7c.

To reduce the noise in the image, a labeling procedure is performed, isolating connected components and eliminating the small ones according to a threshold related to the bounding box dimension (figure 7d). The six lines delimiting the two concentric triangles are detected using Hough transform. We found that generating a line for each blob detected may introduce noise: two or more blobs, referred to the same category, could be split (figure 8a), because of the presence of discontinuities or partial occlusion of the road sign; this separated blobs involve the generation of
similar lines that affect the shape detection (figure 8b). To

Fig. 8. (a) Label image with split blobs. (b) Application of the Hough transform generating a line for each blob detected.

avoid this Hough transform is applied on the Sobel norm image, processing distinctly points of different categories and considering at the same time points belonging to blobs relative to the same category. Six different Hough images are computed, for each considered category, only evaluating nonzero pixels of the Sobel norm image, belonging to a valid blob. In order to obtain more accurate results, reducing the noise contributions, we also calculate a weighted Hough transform, evaluated considering the intensity of the edge variation described by every pixel of the Sobel norm image. Considering the maximum values of the Hough transforms, the algorithm detects at most six lines (figures 9a, 8b, 8c): the presence of slight edges could causes the absence of blobs for a category involving the generation of less than six lines (figure 9d).

In order to crop the area to be processed by the neural network, the vertices generated by the intersections of the lines delimiting the inner triangle are detected. If the lines obtained by the Hough transformation are six, we search the three pairs of them delimiting the thick red edge of the sign; i.e. pairs of ideal parallel lines, with distance between phases equal to $\pi$ are searched. Otherwise when the number of lines obtained is less than six, at least three lines with three different orientation are detected in order to obtain through their intersection a pattern of sides compatible with a triangle: in figure 10 are shown all valid configurations for the generation of triangular shapes. Configurations (c) and (f) in the figure 10 are formed by sides of the same type (i.e. they are all sides of the inner triangle or all edges of the outer triangle). The other combinations are generated by two sides of same the triangle (inner or outer) and one of a different type (outer or inner).

Basing on this considerations, we are able to find what type of pattern the three detected lines form: the position of their intersection points defines the orientation of the triangle while the information about mutual gap between the peaks of the phase distribution and the orientation, allow to recognize the type of side (i.e. inner or outer). Then we consider the intersections between the detected lines in order to find the three vertexes delimiting the inner triangle: if one of the three detected sides is referred to the inner triangle, while the other two belong to the outer triangle (figure 11a), two vertexes (i.e. those generated respectively by the intersection between each outer side and the inner side) are shifted along the line relative to the inner edge, while the third point (i.e. the intersection between the two outer sides) will be shifted of a distance according to the thickness of the red edge defined in the technical specification for the triangular road signs [17]. Otherwise if two of the detected sides define the inner triangle, and the remaining one is referred to the outer triangle (figure 11b), only two vertexes should be shifted along the internal lines (i.e. those placed on the base of the triangle). When the detected lines do not generate a pattern compatible with the presence of a triangle, bounding box is hold as invalid, considering that it does not frame a triangular shape.

**B. Rectangles**

If the analysis of the Sobel phase gap leads to suppose the presence of a rectangle, the same approach used for the triangles detection is applied, unlike the number of sides to search. Since rectangular sign do not have a colored thick border as the triangular ones, it is only necessary search 4 sides, one for each edge of the sign. The categorization (figure 12f) is performed considering four possible categories; the obtained lines (figure 12b) are valid if their mutual position defines a rectangle.
V. RESULTS

The algorithm has been deeply tested on different scenarios frames leading robust results: all categories of triangular (figures 13a, 13b, 13c, 13d, 13e) and rectangular (figures 13f, 13g, 13h) signs are correctly detected. The presence of slightly illuminated sign (figure 13c) does not affect the detection performances. As shown in figure 14 the presented approach allows the detection of rotated signs, both in presence of small rotations (figures 14a, 14b, 14c, 14d) and heavy rotations (figures 14e, 14f, 14g, 14h). The system has been tested in both case of vertical rotation, due to a misplacement of the road sign and in case of horizontal rotation that will result in a rotation due to the perspective effect. The detection succeeds both with vertically (figures 14a, 14b, 14c, 14d, 14f, 14g) and horizontally (figures 14e, 14h) rotation of the signs.

In figure 15 are shown two cases of false positives where the stripes placed on the trash bin (figure 15a) and two trees in front of a red building (figure 15b) generate patterns compatible with the presence of a priority sign. The presence of these false positives could be mitigate analyzing the positions of the elements with respect to the road in order to verify that they are set in a place compatible with that of a road sign.

VI. CONCLUSIONS

The presented approach allows an improvement of the classification performance, since the crop of the inner area for triangular shapes is obtained considering the edges of the detected sign rather than using a fixed shape mask. This allows to correctly detect a sign also in case that its bounding box is not centered on it. Compared to pattern matching, the algorithm yields better results in presence of rotated and deformed signs, with an increase of only 10% of execution times; anyway the computational overhead requested ensure the real-time application of the system. Compatibly with the acquisition system, in a typical setup the algorithm is able to detect a road sign from a maximum distance of 30 metres until the vehicles pass it. Since the performed analysis of the Sobel edges has demonstrated that the phase distribution of the real circular signs does not follow the ideal trend, described method is not suitable for circular sign detection; then futures development will regard the recognition of this type of sign; a possible approach could be that described in [18], that is based on the using of the generalized Hough transform.


