AUTOMATIC DETECTION AND CLASSIFICATION OF TRAFFIC SIGNS

Carlos Filipe Paulo, Paulo Lobato Correia

Instituto de Telecomunicações, Instituto Superior Técnico, Av. Rovisco Pais, 1049-001 Lisboa, Portugal
Phone: +351-218418462, Fax: +351-218418472, e-mail: {cfp, plc}@lx.it.pt

ABSTRACT

This paper proposes algorithms for the automatic detection of traffic signs from photo or video images and their classification to provide a driver alert system. Several examples taken from Portuguese roads are used to demonstrate the effectiveness of the proposed system.

Traffic signs are detected by analyzing color information, notably red and blue, contained on the images. The detected signs are then classified according to their shape characteristics, as triangular, squared and circular shapes. Combining color and shape information, traffic signs are classified into one of the following classes: danger, information, obligation or prohibition. Both the detection and classification algorithms include innovative components to improve the overall system performance.

Index Terms— Traffic sign detection, color image analysis, shape analysis

1. INTRODUCTION

Road traffic assumes a major importance in modern society organization. To ensure that motorized vehicle circulation flows in a harmonious and safe way, specific rules are established by every government. Some of these rules are displayed to drivers by means of traffic signs that need to be interpreted while driving. This may look as a simple task, but sometimes the driver misses signs, which may be problematic, eventually leading to car accidents. Modern cars already include many safety systems, but even with two cars moving at 40 km/h, their collision consequences can be dramatic. Although some drivers intentionally break the law, not respecting traffic signs, an automatic system able to detect these signs can be a useful help to most drivers.

One might consider a system taking advantage of the GPS system. It could be almost flawless if an updated traffic sign location database would be available. Unfortunately, few cars have GPS systems installed and traffic sign localization databases are not available for download.

Installing a low price "traffic sign information" receiver on a car could also be a good idea if traffic signs were able to transmit their information to cars. But, such system would be unpractical, requiring a transmitter on each traffic sign.

A system exploiting the visual information already available to the driver is described in this paper. It detects and classifies traffic signs by analyzing the images/video taken from a camera installed on the car.

Automatic analysis of traffic sign information from video images can be divided into three distinct stages [1, 2, 3]. A detection stage, in which the most likely image areas to contain traffic signs are searched for. These areas are often known as regions of interest (ROI). The classification stage tests each ROI to classify it into one of the traffic signs categories, such as obligation or prohibition. Finally, recognition will identify the specific sign within its category. Additionally, when dealing with video, the literature often considers a tracking stage, which, although not essential, allows a faster detection of ROIs and better sign classification and recognition, by exploiting information from several images.

For the detection stage, color is often the main cue explored to find the areas where traffic signs appear [2, 4-7], a process known as color segmentation. In fact, the color of the paint used on signs is defined *a priori*. Nevertheless, color appearance may change depending on the hour of the day, weather and illumination conditions, such as direct sun light exposure. RGB images are usually converted to another color space for analysis, to separate color from brightness information. The color spaces most often used include L*a*b [3], CIECAM97 [4] and HSV [5].

Since traffic signs follow strict shape formats, the classification stage usually starts by testing each detected ROI's geometric properties. Edge and/or corner detection methods are often used for shape detection [6, 7]. Cross-correlation based template matching with road sign templates (circle, triangle, octagon and square) [3], genetic algorithms [5], Haar wavelets [1] or FOSTS model [4] have also been used for this purpose. Finally, the sign contents are analyzed, comparing each ROI with a model using template matching [3] or a trained back-propagation neural network [6], allowing the traffic signs to be recognized.

For tracking, solutions based on the creation of a search window around the previous sign temporal position have been considered [2, 3]. However, the usage of Kalman filters for tracking is often considered more reliable [7].

The main goal of this paper is to detect and classify traffic signs into one of the classes: danger, information, obligation and prohibition classes. Danger and prohibition signs are characterized by a red border, obligation and information

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signs by a blue border.

Therefore, color can be exploited for the detection of signals, as discussed in Section 2. Section 3 addresses the classification into each of the considered classes, exploring color, shape and salient points of the detected ROIs. Section 4 presents detection and classification results for images captured from Portuguese roads and Section 5 offers some conclusions.

The paper includes contributions to make detection robust, such as a fuzzy detection of the color areas corresponding to candidate signs, the ability to not discard signals detected as several disconnected areas, or the shape classification.

2. TRAFFIC SIGNS DETECTION

The detection of traffic signs, assumes a crucial role in any traffic sign recognition application. In fact, a sign that is not correctly detected cannot be classified and recognized to inform the driver. For instance, when the sign area is not completely detected, bad classification and recognition are likely to occur.

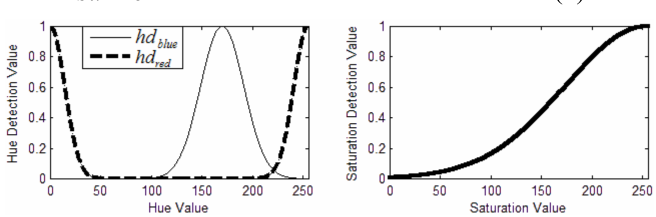
As stated in the introduction, color is explored for sign detection. Each input image is converted to the HSV color space, as it allows decoupling the color and intensity information. Red and blue color regions are identified in the input images by analyzing the hue (H) component. The saturation (S) component is also used, as for very low saturation values the color information is no longer reliable.

This paper proposes using a fuzzy detection of the relevant H and S values. For each pixel, a hue-based detection (*hd*) of the blue and red colors is done, according to equations (1), where hd_{blue} gives a value close to one for blue regions and hd_{red} has a similar behavior for red regions. As H has values in the [0-255] range, values for red are close to 0 or 255, while for blue the values of interest are close to 170.

A saturation detection (*sd*) value is found by analyzing the S channel (equation 2). The curves corresponding to the detection of the hue values corresponding to blue and red, as well as for saturation detection, are illustrated in Figure 1.

$$hd_{blue} = e^{\frac{-(x-170)^2}{30}}, \quad hd_{red} = e^{\frac{-x^2}{20^2}} + e^{\frac{-(x-255)^2}{20^2}} \quad (1)$$

$$sd = e^{\frac{-(x-255)^2}{115^2}} \quad (2)$$



(a) (b)

Figure 1 – (a) Functions for detection of red and blue image areas; (b) Function for detection of color saturated areas

The output of the hd_{blue} or hd_{red} detection functions, with values between 0 and 1, is multiplied with the *sd* output value, yielding an initial detection value (*hs*) for each pixel. Non-sign regions will have low values, being discarded by setting their value to 0. The remaining values are rescaled in a non-uniform way, according to equation (3), to enhance the importance of higher values and reduce that of lower ones to form an auxiliary image (*hsn*) that will be used to select the threshold T_{hs} to apply to *hs* for detecting candidate sign regions.

$$hsn = \begin{cases} 0 & hs < 0.3 \\ \left(\frac{hs-0.3}{0.7-0.3}\right)^2 & 0.3 \le hs < 0.7 \\ 1 & hs \ge 0.7 \end{cases} \quad (3)$$

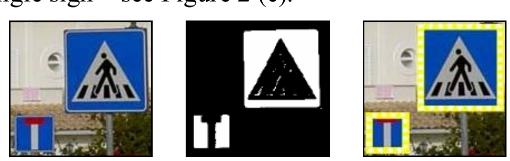
The threshold level T_{hs} is obtained by applying Otsu's algorithm [8] to *hsn*, and then used on the *hs* image, creating a binary map of candidate sign regions. Each resulting connected region is marked as a possible sign, and will be tested further in terms of its size and aspect ratio. Too small or too big regions are discarded, as signs of interest to the driver should appear with an average known size.

Assuming signs are not too much rotated or damaged and knowing that allowed shapes are triangles, squares, octagons or circles, the width of a sign is expected to be very similar to its height. Any such region that has its mass center near the centre of the region is considered as a possible sign.

Occasionally, the described color segmentation may split sign regions into two regions. Typical examples are *STOP*, *Dead End* and *No-Entry* signs, for low resolution images. An example for a *Dead End* sign is shown in Figure 2 (a). The blue color detection output image splits the *Dead-End* sign into two disconnected regions – see Figure 2 (b).

To be able to effectively join the two halves of the same sign, the shape of each candidate's region bounding box is tested. Sign halves are expected to have rectangular bounding boxes, not squared. For all rectangular regions, a test of their white areas and of the respective centers of mass is done. Two halves of the same signal should present similar areas, as signals have symmetric shapes, and the centers of mass should be close to each other and correctly aligned. When all requirements are met, the two regions are merged and considered as a single sign.

In the example of Figure 2, the rectangular bounding boxes of the signal halves have similar size and area. As their height is larger than width, and the vertical position of the centre of mass is similar, the two fragments are merged into one single sign – see Figure 2 (c).



(a) (b) (c)

Figure 2 – (a) Image including Dead End sign; (b) Output image after blue color detection algorithm; (c) Detection result

Finally, any region contained within another region is discarded as a probable mistaken (partial) detection. The shape of all ROIs that meet all the requirements are handed for further processing by the classification stage.

3. TRAFFIC SIGN CLASSIFICATION

The classification module takes the detected ROIs and classifies them into one of the considered classes: danger, information, obligation or prohibition, or as a non-sign. Also Yield and STOP signs are recognized as special cases.

Each of the ROIs' binary map is separately evaluated at this stage. For optimization purposes, ROIs may be resized, if needed, to a maximum of 50 pixels wide. Then, each ROI's shape is tested, and a probability value of having triangular, squared or circular shapes is assigned. If at least one shape has high probability (above 75%), the highest valued shape is assumed for that sign. Otherwise, that ROI is classified as a non-sign region and it is discarded. The final classification into one of the considered classes is done taking into account both shape and color information. The methods for shape classification are discussed in the next sub-sections.

3.1. Circle Shape Identification

For circle identification, each ROI is scanned using the fast radial symmetry detection method (FRS) [9]. If a circular shape is present, the FRS output will contain high values on the circle's central area. In ideal conditions, only the center pixel of the output image would need to be tested, but for real images all pixel values inside a square region, around the output center, are analyzed. The size (*sz*) of the squared region used is 20% of the largest dimension (width, *ow*, or height, *oh*) of the output image, as shown in Figure 3.

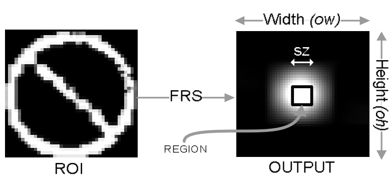


Figure 3 - Circle classification process

Within this squared central region, all pixel values are averaged (*avg*). That average is divided by the maximum (*max*) output value, resulting in a circle probability (*cp*), according to equation (4).

On Figure 3's example a *cp* value of 88.5% was obtained.

$$cp = \begin{cases} 0 & max < 0 \\ avg & 0 < max < 1 \\ \dfrac{avg}{max} & max > 1 \end{cases} \tag{4}$$

3.2. Triangle and Square Shape Identification

Triangular and squared shapes are identified by finding the corners of each ROI, using the Harris corner detection algorithm [10]. The existence of corners is then tested in six different control areas of the ROI, as illustrated in Figure 4. Each control area value (*tl, tc, tr, bl, bc, br*) is initialized to zero. When a corner is found inside a control area, the respective value (0.25 for vertices and 0.34 for central control areas) is assigned to that control area value.

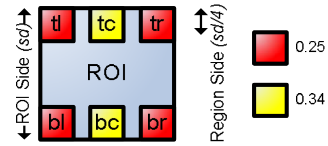


Figure 4 - Regions tested for corner occurrence

The probabilities that a given ROI contains a square (*sqp*), a triangle pointing up (*tup*) and a triangle pointing down (*tdp*) are computed according to equations (5, 6, 7).

$$sqp = tl + tr + bl + br \tag{5}$$

$$tup = 1.32 \times (bl + br) + tc - 1.1 \times (tl + tr) \tag{6}$$

$$tdp = 1.32 \times (tl + tr) + bc - 1.1 \times (bl + br) \tag{7}$$

Figure 5 shows an example of the detected corners on the blue sign of Figure 7 (a). Only the top right and bottom center control areas contain no corner occurrences, keeping value zero. For this sign, *cp* is 15.5%, *sqp* 75%, *tup* 72.5% and *tdp* 0%, correctly resulting on a square identification.

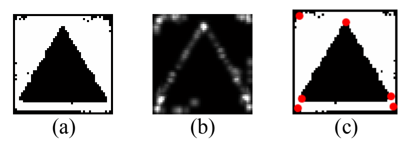


Figure 5 - (a) Input ROI image; (b) Corner detector result; (c) Input ROI image with detected corners

For the example of Figure 3, *sqp* scored 0% and both *tup* and *tdp* had a value of 34%. In this case, only the circle probability scored at least 75%, and the sign was correctly identified as a circle.

3.3. Traffic Sign Classification

After color and shape information is known, signs can be classified into the considered classes, as shown in Figure 6. The *Yield* sign is recognized as the only red colored sign with triangular pointing down shape. The *STOP* sign is also recognized, as having a ROI containing more than 50% of red pixels and not presenting triangular or circular shapes. Classification examples are provided in section 4.

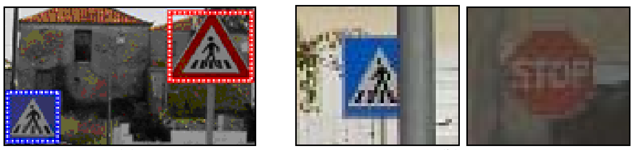
COLOR \ SHAPE	△	▽	□	○	⯃
BLUE			INFORMATION	OBLIGATION	
RED	DANGER	YIELD SIGN		PROHIBITION	STOP SIGN

Figure 6 - Traffic sign classification into the considered classes

4. RESULTS

The database used for tests is composed of photos taken along Portuguese roads. For this paper a total of 579 traffic signs were considered, of which 218 presented low luminosity, 344 good and 17 excessive luminosity.

Applying the sign detection method detailed in section 2 correct detection rates of 93.1%, 97.7% and 29.4% were achieved for each lighting condition, corresponding to a total of 94% correctly detected signs. The missed detections occur for signs partially occluded or presenting unexpected color characteristics due to environmental conditions. Additionally, 698 other regions were detected as candidate signs (ROIs), 82.3% of which being too small to be considered for the classification stage, thus being discarded, and 17.7% not corresponding to real signs. The remaining sign and non-sign ROIs will be further tested. Detection examples are presented in Figure 7.



(a) (b)

Figure 7 - Examples of (a) correctly detected and (b) missed signs.

In terms of the classification algorithm, the proposed circle identification method correctly classified 82.9% of the circle shaped signs (Figure 8 a). Most of the classification errors happened for signs appearing too big in the image.

For square shapes a correct identification rate of 91.4% was obtained (Figure 8 b). Triangular signs presented the best results, with 95.0% correct identification rate (Figure 8 c). The current method for *STOP* recognition is very simple, often wrongly identifying these signs as circles (46.7%) whenever the *STOP* sign appears with low resolution.

The classification algorithm is robust for signs presenting some geometric distortions, graffiti and partial occlusions where the sign appears divided in two halves – see Figure 8.

Tables 1 and 2 present some statistics for the detection and classification stages.

Table 1 - Sign detection results

Luminosity	Present Signs	Detected Signs	Detection Rate	Overall Detection
Low	218	203	93.1%	94%
Normal	344	336	97.7%	
Excessive	17	5	29.4%	

Table 2 - Detection and classification results for each sign class

Class/Sign	Detection Rate	Classification Rate	Global Rate
Danger	93.1%	94.0%	87.5%
Information	97.1%	91.4%	88.8%
Obligation	94.0%	92.1%	86.7%
Prohibition	95.6%	79.1%	75.6%
STOP	93.8%	53.3%	50.0%
Yield	89.2%	97.0%	86.5%

The average processing time was of 2.285 seconds/image on a Pentium 4 at 3 GHz, for 800x600 input images. The processing time can be considerably reduced by using smaller sized images. For 400x300 images signs near the camera achieve similar results; but further away signs tend to be undetected or unclassified due to the lower resolution.

(a) (b) (c)

Figure 8 - Result after classification. (a) classified as circles; (b) classified as squares; (c) classified as triangles.

5. CONCLUSION

This paper proposed an automatic traffic sign detection and classification system. New contributions are included for the validation of sign detections, as well as for the classification stage, namely by including a simple, yet effective, algorithm for square and triangle identification.

As expected, correct traffic sign detection is essential for accurate classification. As future work, the detection algorithm will be improved to better handle images with critical illumination conditions, such as those obtained from night driving. Also improved classification for STOP signs and the recognition stage will be added. For normal illumination conditions, the algorithm already shows good performance in terms of detection and classification.

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