# AUTOMATIC DETECTION AND CLASSIFICATION OF TRAFFIC SIGNS

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**ABSTRACT**

This Thesis proposes algorithms for the automatic detection of traffic signs from photo or video images, classification into danger, information, obligation and prohibition classes and their recognition to provide a driver alert system.

The used algorithm was optimized to detect, classify and recognize ideal signs of a Portuguese database sign and slightly tuned after real sign testing. 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. The recognition of traffic signs is done by comparing the pictogram inside of each sign with the ones of the database. This proved to be the most time consuming stage of the process, proving that classifying signs into classes is essential for reducing the recognition time.

***Index Terms—*** Traffic sign detection; Color image analysis; Shape analysis; Feature extraction.

## 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 Thesis. 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]. Crosscorrelation 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 Thesis is to detect and classify traffic signs into one of the classes: information, danger, obligation and prohibition classes. Danger and prohibition signs are characterized by a red border, obligation and information signs by a blue border. Also the recognition of each specific sign is an objective of this Thesis, being the most time consuming routine, as such it is only done for signs of the respective class. Exceptionally, the *Yield*, *Wrong-Way* and *STOP* signs are detected and recognized, not being classified into one of the four previously referred classes.

The procedure adopted in this Thesis can be divided into three stages: detection, classification and recognition (see Figure 1). In the detection stage, color information is exploited to detect regions of interest (ROI) that may correspond to traffic signs. The shape of these regions is tested in the classification stage, allowing rejecting many of the initial candidates and grouping traffic signs into classes. Finally, the pictogram contained on each ROI (if exist) is extracted, analyzed and compared with the pictogram database. The best match between the ROI and database pictogram, if high enough, is considered the sign that is more likely to appear in that ROI. Each recognized sign is part of the output result of the recognition stage.

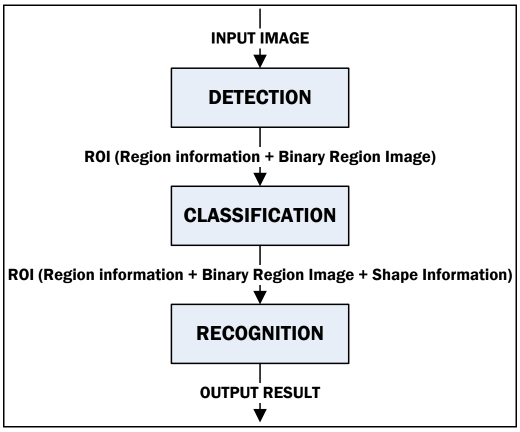



**Figure 1 - Flowchart of the proposed system**

It has been said that the procedure adopted in the Thesis consists in three different stages. Detailed information of detection, classification and recognition stages are described in chapters 2, 3 and 4, respectively. Chapter 5 provides detection, classification and recognition results for the database signs and also for real signs found on the images captured from Portuguese roads. Chapter 6 offers some conclusions.

The Thesis includes contributions to make detection robust, e.g., avoiding to discard signals that appear as several disconnected areas. Also, a fast and reliable circle, triangle and square shape classification is presented. Finally, a method to extract the pictogram information of signs is described.

## 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. The HSV color space allows decoupling the color and intensity information. Taking advantage of the HSV color space, each pixel of the input image is converted using a hue-based detection of the blue and red colors, according to equations (1) and (2), where $hd_{blue}$ gives a value close to one for blue regions and $hd_{red}$ has a similar behavior for red regions. The saturation (S) component is also used, as for very low saturation values the color information is no longer reliable (see equation 3).

$$hd_{blue} = \begin{cases} 1 - \dfrac{|R-G|}{MAX-MIN}, & (MAX = B) \wedge (MAX - MIN \geq th) \\ 0, & otherwise \end{cases} \quad (1)$$

$$hd_{red} = \begin{cases} 1 - \dfrac{|G-B|}{MAX-MIN}, & (MAX = R) \wedge (MAX - MIN \geq th) \\ 0, & otherwise \end{cases} \quad (2)$$

$$S = \begin{cases} 0, & MAX = 0 \\ 1 - MAX, & otherwise \end{cases} \quad (3)$$

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. An example of the color segmentation process is presented at Figure 2:

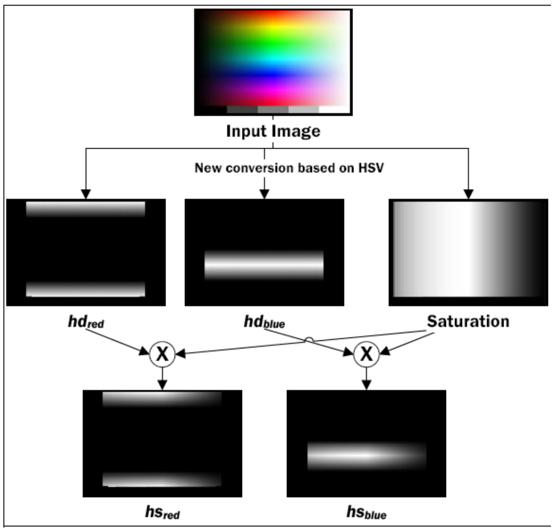



**Figure 2 - Example of the color segmentation process**

Each color segmentation image (hsred and hsblue) is binarized (i.e., thresholded), so that the resulting '1' valued pixels correspond to sign color and other pixels take value '0'. The resulting binary image usually contains more than one detected region, where a region is considered to be any group of 8-connected '1' valued pixels (see Figure 3). To easily identify each region a label is attributed to each one, resulting in a labeled image. Finally, a set of important region features is acquired for further processing.

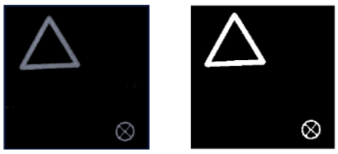


**Figure 3 - Binarization example**

Each resulting connected region is marked as a possible sign, and it will be further analyzed according to Figure 4:

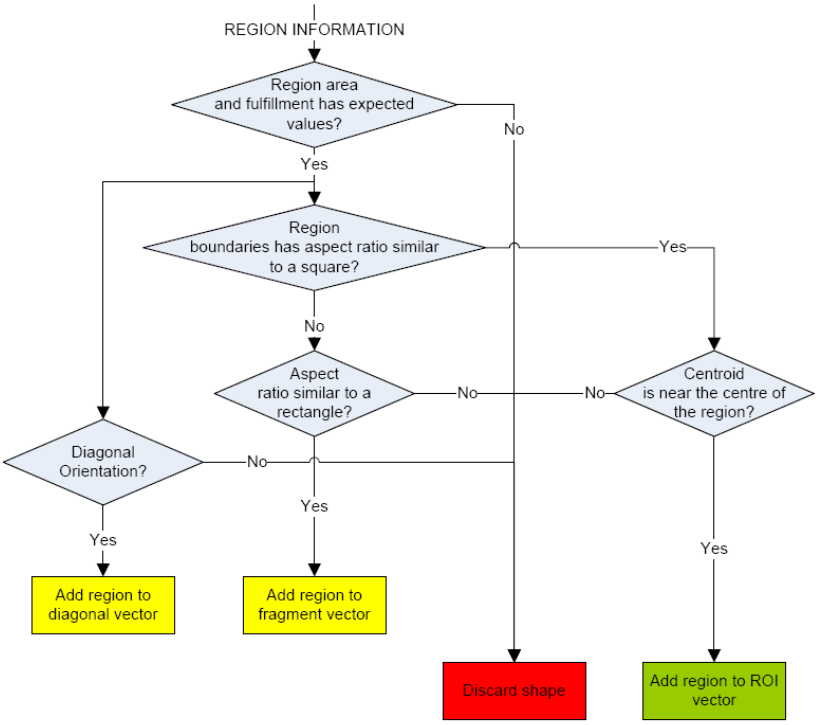



**Figure 4 - Flowchart of region analysis**

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 5 (a). The blue color detection output image splits the *Dead-End* sign into two disconnected regions – see Figure 5 (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 5, 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 5 (c).

(a) (b) (c)

**Figure 5 - (a) Image including *Dead-End* sign,**
**(b) Output image after blue color detection algorithm, (c) Detection result**

The same strategy is used for signs that always appear disconnected after the labelling process. This happens for blue signs containing a red diagonal strip, also known as end of obligation signs, as shown on Figure 6.

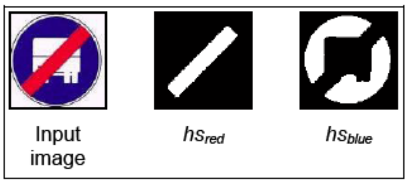



**Figure 6 - Color components of an end of obligation sign**

For these cases, the orientation of each part is taken into account, since it can be distinguish by that property (see Figure 7). To successfully merge these 3 regions into a single sign, a red diagonal region must be present in addition to two blue diagonal regions.

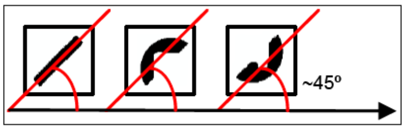



**Figure 7 - Region orientation of an end of obligation sign**

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*, *Wrong-Way* 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.

### Circle Shape Identification

For circle identification, each ROI is scanned using the fast radial symmetry detection method (FSR) [9]. If a circular shape is present, the FSR 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 8.

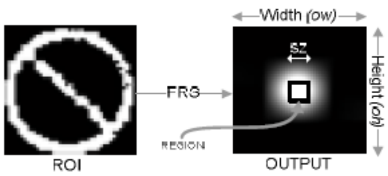



**Figure 8 –Circle classification process**

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.

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

**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 9. 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.

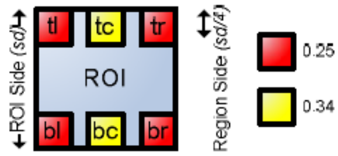



**Figure 9 - Regions tested for corner occurence**

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).

$$sqp = tl + tr + bl + br \tag{5}$$
$$tup = 1.32 \cdot (bl + br) + tc \; \square 1.1 \cdot (tl + tr) \tag{6}$$
$$tdp = 1.32 \cdot (tl + tr) + bc \; \square 1.1 \cdot (bl + br) \tag{7}$$

Results of the proposed algorithm are presented in the following tables 1 and 2:

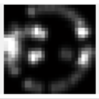
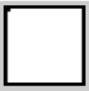
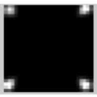
| Example number | Input ROI | Corner detector result | *sqp* | *tup* | *tdp* |
|---|---|---|---|---|---|
| 1 |  |  | 0% | 0% | 0% |
| 2 |  |  | 100% | 11% | 11% |
| 3 |  |  | 50% | 100% | 0% |
| 4 |  |  | 50% | 0% | 100% |
| 5 |  |  | 0% | 0% | 0% |

**Table 1 - Square and triangle classification results**

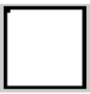
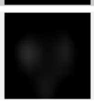
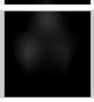
| Example number | Input ROI | FRS Output | *Cp* |
|---|---|---|---|
| 1 |  |  | 94.2% |
| 2 |  |  | 25.8% |
| 3 |  |  | 4.9% |
| 4 |  |  | 7.2% |
| 5 |  |  | 94.1% |

**Table 2 - Circle classification results**

**Traffic Sign Classification**

After color and shape information is known, signs can be classified into the considered classes, as shown in Figure 10. The *Yield* sign is recognized as the only red colored sign with triangular pointing down shape. The *Wrong-Way* and *STOP* sign are also recognized, as having a ROI containing more than 50% of red pixels and not presenting triangular or circular shapes. To distinguish each, the middle area of the sign is tested. If a white stripe is found, the sign is recognized as the *Wrong-Way* sign; otherwise it is recognized as a *STOP* sign.

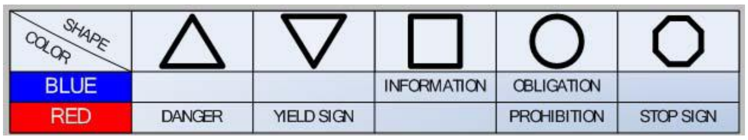



**Figure 10 - Traffic sign classification into the considered classes**

## 4. RECOGNITION

After sign detection and their classification into classes, comes the recognition stage, where each ROI will be identified as a concrete sign. The pictographic content of signs is what distinguishes each sign, within its class and it will be analyzed for recognition purposes.

A block diagram illustrating the procedure used to recognize a sign is presented in Figure 11. It starts by extracting the pictogram information of each ROI. If the resulting pictograms have two or more disconnected regions they are connected together, to obtain a representation consisting of a single (and unique) contour for each sign. Then, the contour information is transformed into contour peak based information, using the curvature scale space (CSS) representation, being matched with the database to find the best candidate.

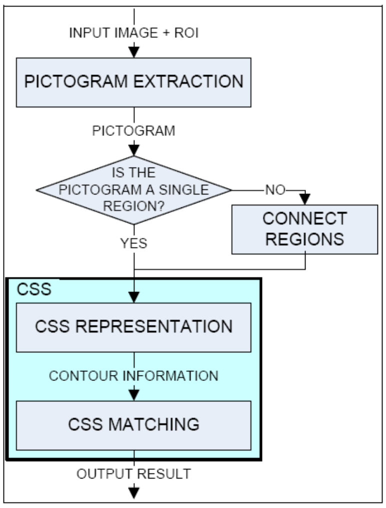



**Figure 11 - Flowchart of recognition**

The block diagram presented in Figure 12 presents the required stages to combine the red and blue segmented regions and the red component of the RGB color space for correctly extracting each sign pictogram. The main objective is to search signs for black pictograms, being any white area considered as white background. If no black pictogram is detected, then the white background is considered as a white pictogram.

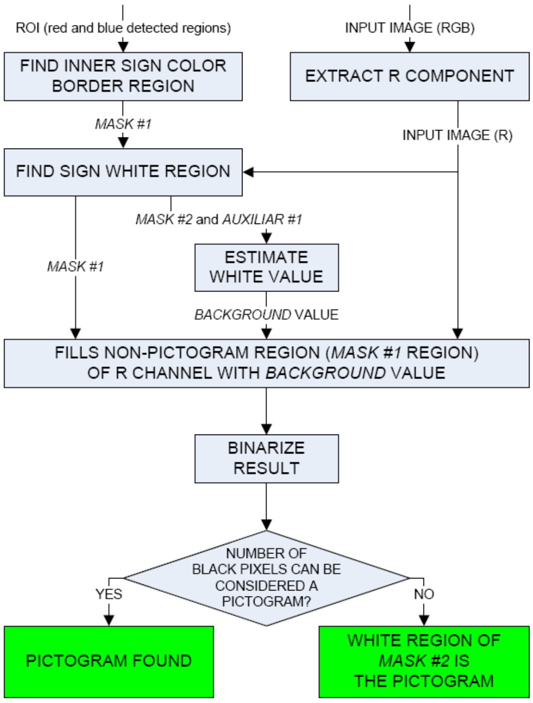



**Figure 12 –Flowchart of pictogram extraction method**

A pictogram extraction example is shown at Figure 13. The input signs (shown in the top) are analyzed, resulting on the correctly extracted pictograms shown on the bottom part of the image.

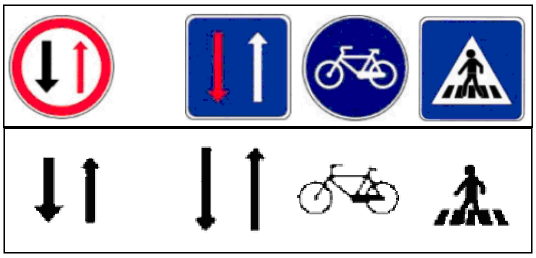


**Figure 13 - Pictogram extraction example**

Each pictogram requires having a single outer contour, so it can be tested using the CSS representation. For that purpose, a snake operation is performed on the pictogram as it is shown at Figure 14. A squared contour starts covering the pictogram, evolves and after some iteration it successfully describe the outer contour of the pictogram.

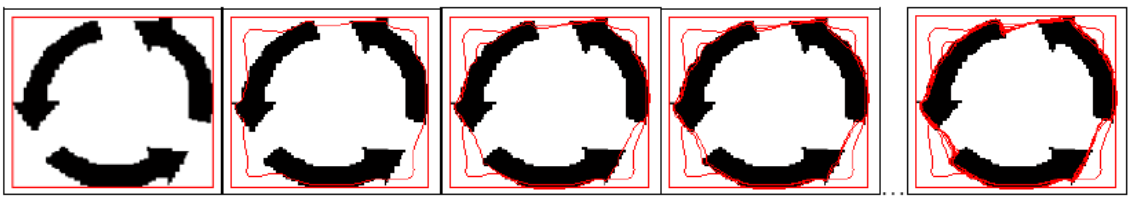


**Figure 14 - Snake iterations allows finding the outer contour of a pictogram**

Finally, the Curvature Scale Space (CSS) is used to transform the outer contour representation into compact information that can be easily used for shape matching.
The CSS is a multi-scale representation that describes object shapes by analyzing a closed contour's shape inflection points. Inflection points are the points where the second derivative changes sign, i.e., the zero-crossing points of the second derivative, or in other words, the points where the contour changes from being concave upwards (positive curvature) to concave downwards (negative curvature), or vice versa.

## 5. RESULTS

The database used for tests is composed of photos taken along Portuguese roads. For this Thesis 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 15.

(a) (b)

**Figure 15 - 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. 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. Triangular signs presented the best results, with 95.0% correct identification rate (Figure 8 c). The classification algorithm is robust for signs presenting some geometric distortions, graffiti and partial occlusions where the sign appears divided in two halves. Tables 3 and 4 present some statistics for the detection and classification stages.

| Luminosity | Present Signs | Detected Signs | Detection Rate | Overall Detection |
|---|---|---|---|---|
| Low | 218 | 203 | 93.1% | 94.0% |
| Normal | 344 | 336 | 97.7% | |
| Excessive | 17 | 5 | 29.4% | |

**Table 3 - Sign detection results**

| Class | 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% | 79.4% | 75.6% |

**Table 4 - Detection and classification for each sign class**

Since recognition takes more time to process, the database tested was smaller, and the results are only taken for successfully detected and classified signs. The results are displayed on the following table:

| | Danger signs | Prohibition signs | Obligation signs | Information signs | Non-classified signs | All Signs |
|---|---|---|---|---|---|---|
| Presented Signs | 33 | 55 | 37 | 77 | 59 | 261 |
| Recognized Signs | 23 | 38 | 31 | 58 | 59 | 209 |
| Recognition Rate | 69.7% | 69.1% | 83.8% | 75.3% | 100% | 80.1% |

**Table 5 - Recognition results**

The recognition rate including all tested sign was of 80.1%, being a value close to the one that resulted when testing the database signs. However, for this test a lot of sign were repeated, since the photos did not contained the variety presented in the database signs, meaning that if a sign that is easily recognized by the method appears often, could improve the recognition rate. By looking at the results, it is obvious that the signs which do not be to be classified and recognized by the normal method, being tested specially, were always correctly recognized and improving the overall recognition rate. Nevertheless, the used photos were randomly chosen and, although the set of photos is not vast, the result gives an approach of how successful is the overall method.

## 6. CONCLUSION

This Thesis proposed an automatic traffic sign detection, classification into four different classes (danger, information, obligation, and prohibition) and also recognition 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. Also, an innovative method to extract the contents of a sign was implemented. That content is then recognized by converting its shape into CSS information and consequently matching with the database information.

As expected, correct traffic sign detection is essential for accurate classification. Classifying each sign into a class allows not only to reduce the error probability, but also reduces the overall method computation time, since the most time consuming routines are done into a smaller set of signs. For daytime photos, the method correctly detects and classifies most of the signs, recognizing well a satisfying amount of signs, since for this Thesis 80% of the signs were successful recognized.

As future work, the detection algorithm could be improved to better handle images with critical illumination conditions, such as those obtained from night driving. Also, a tracking method could improve dramatically the sense of which sign was really recognized.

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