Fast greyscale road sign model matching and recognition

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Abstract. Mobile Mapping is a standard technique for compiling cartographic information from a mobile vehicle. This paper proposes a novel method for modelling the recognition in a Mobile Mapping process that consists in fitting a model to recover the sign distortion and applying recognition techniques on weak classifiers cascade results. The images received from Adaboost learning algorithm with weak classifiers cascade are processed to capture the sign and to perform the following recognition. Radial symmetry, false contours extraction techniques, and ellipse fitter algorithms are used to solve the problem of signs distortion. The procedure is robust even in the case of high variance of sign appearance as noise, affine deformation, and reduced illumination.

Keywords. Mobile Mapping, Radial Symmetry, Road Sign Recognition.

1.Introduction

High variance of sign appearance has made the detection and recognition of road signs a computer vision problem over which many studies have lately been performed. There are two main approaches in this field, the color-based and the grayscale-based sign recognition. Color-based approach allows to reduce false positives results in the recognition process whereas grayscale methods concentrate on the geometry of the model to recognize it.

The color-based studies are based on segmentation by thresholding in color space [1][2][3][4]. Ghica [5] study focused exclusively on neural networks that are used for image filtering and sign recognition, while other approaches are based on genetic algorithms [6]. The studies on gray-scale images use geometric reasoning [7][8] and most of them on the Hough transforms, and usually color is used as a complementary technique to eliminate false positive results of the classification method.

We divide our work on road sign analysis in three phases: detection, model matching, and recognition. This paper proposes a way to solve the problem of road sign recognition using a previous Adaboost weak classifiers cascade. We use as input images the results obtained in [9], where the authors use the former algorithm to obtain the detection of road signs. This paper shows how to solve the problem of model fitting and recognition for distorted signs on greyscale images using geometric reasoning. We obtain robust results in the high variance of sign appearance that can be found due to affine deformations (as can be scale, translation, and shearing), noise, partial occlusions, and lightning changes without need to use colour information. The paper is organised as follows:

2.Sign recognition

With the purpose to perform a better approach to the recognition, we divide the problem of sign recognition in three phases: detection, model matching and recognition.

2.1 Detection by Adaboost

The Adaboost algorithm presents a general framework to combine classifiers in order to solve the supervised pattern recognition problem [10]. This approach consists of a) choosing a (weak) classifier, b) modifying example weights in order to give priority to examples where the previous classifiers fail, and c) combining classifiers in a multiple classifier. As a result, each state of the boosting process, which selects a new weak classifier, can be viewed as a feature selection process where features correspond to the image pixels values [11]. The input images of our recognition procedure are provided by the weak classifiers cascade detection process [9].

2.2 Model matching

Given an image where the Adaboost learning algorithm detected a road sign, a region of interest (ROI) that contains a sign is determined (circular in this case, figure 1(a)). However, since we miss information about sign scale and position, before applying recognition we need to apply a spatial normalization. Concerned with the correlation of sign distortion, we look for affine transformations that can perform the spatial normalization to improve final recognition.

2.2.1 False contours extraction

The main problem is to fit a centred sign to the ROI received from Adaboost learning algorithm. Our goal is to cope with the distortion shapes before proceed with the recognition. First, Canny contours detector is applied (figure 1(b)) followed by suppressing unrelevant contours by model fitting. The main idea of the method is that in a contour map extracted from the reduced ROI where the sign is contained, the length of continuous sign contour extracted from Canny detector should be maximal compared to the false contours contained. The method selects relevant contours discriminating them by their length. Figure 1(c) shows the result of the method application for two different input signs.

2.2.2 Radial symmetry

For road sign detection problem we can use the symmetry properties of certain signs to detect points of interest, having a symmetrical arrangement of radiating parts about a central point, or using image gradient direction convergence to locate points of high radial symmetry [12]. We receive a reduced image where the sign is almost centered, so, for the detection of ellipsoidal signs we can use their property of symmetry. The remaining false contours of the first method could be eliminated by a simple horizontal and vertical symmetry intersection from the central point. The process is based on maintaining the points of contour located in two regions to the same distance with respect to a center line. With this fact, we maintain the points of interest and suppress the non-symmetrical points in the image. Figure 1(d) shows the result of the method application for two different input signs.

2.2.3 Ellipse fitting

At this moment and still being lost some points of sign contour, we proceed with a process of fitting an ellipse due to the fact that depending on the point of view circular signs deform to elliptical shapes [13]. All input image contour points are considered in the fitting process, so the previous methods are appropriated to remove the false contours and keep the ellipse fit to the contour points. The objective is to find the parameters of the following function:

$$F(x,y)=ax^2+bxy+cy^2+dx+ey+f$$

so that they define an ellipse. First, we construct the design matrix D that has as many rows as number of contour points are considered in the ellipse fit process, and each row of six elements has the form $[x_i x_i \ \ x_i y_i \ \ y_i y_i \ \ x_i \ \ y_i \ \ 1]$, where (x_i,y_i) represents the coordinates of each contour point. The following step is to construct the scatter matrix:

$$S=D^T D$$

Starting from the constraint matrix $C_{6x6:}$

$$\begin{pmatrix} 0 & 0 & 2 & 0 & 0 & 0 \\ 0 & -1 & 0 & 0 & 0 & 0 \\ 2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{pmatrix}$$

introducing the Lagrange multiplier λ, and considering the vector V=[a b c d e f], we can find the fit ellipse parameters solving the following system:

$$\begin{aligned} SV&=\lambda CV \qquad (1) \\ V^T CV&=1 \end{aligned}$$

This system is readily solved by considering the generalized eigenvectors of (1). The ellipse fit parameters correspond to the six elements from the only negative eigenvalue. As a result of this method, we capture the sign and correct sign distortion in order to proceed with the recognition phase (figure 1(e)). For more details see [13].

2.3 Recognition

One of the classic classification methods applied when no information about data distribution is available is the nearest neighbour classification in the image space. Under this scheme, an image in the test set is recognized by assigning to it the label of most of the closest points in the learning set. If all images are normalized to have zero mean and unit variance, then this procedure is equivalent to choosing the image in the learning set that best correlates with the test image. Because of the normalization process, the result is independent of light source intensity and the effects of a video camera automatic gain control [14][15]. We use the k-nearest neighbour algorithm and the equalization of gray image level as normalization factor for ellipsoidal signs classification.

3.Results

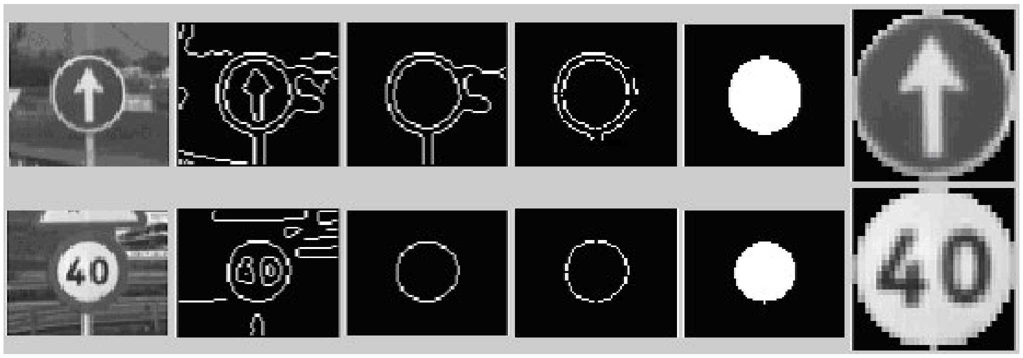
In order to analyze the robustness of the exposed methods, we perform a set of tests in order to show their robustness. We comment the fitted parameters for each one of the methods and the results of the complete recognition process.

3.1 Methods parameters

The input images we obtain by the detection process in [9], were previously yielded by the *Institut Cartogràfic de Catalunya*'s Geomòbil project vehicle, that includes an image capture subsystem based on a pair of digital cameras of 1024 x 1024 pixels [16]. This input image has a maximum resolution of 100 by 100 pixels, and it contains a circular road sign of size al least of 24 by 24 pixels. Basing on these data, the minimum size sign to recognize has an approximated perimeter of 75 pixels. For the extraction of contours of length inferior to 50 pixels, we extract the greater amount of false contours of the sign, which could be at different scales, maintaining the edge of the sign, considering partial occlusions or light losses of contour due to the confusion of the gray levels between the background and the sign.

About the application of Radial Symmetry, we consider the horizontal and vertical symmetry of the image from the central point, which corresponds as well to the center of the sign. Due to the imprecision of Canny detector we need to apply a tolerance of ± 2 pixels in the process of estimating symmetrical points. In order to suppress some concentrated false contours that could remain in the center of the image after the application of the 2 previous methods, we apply a circular mask of radius 8 pixels that we estimated in an empirical way. This mask is applied on the center of the image, since in no case we lose sign contour points because of the minimum size of the input sign. At the ellipse fitting step, all the contour points that were not previously eliminated are used, having only to apply the previously exposed formulas to find the 6 parameters that define the ellipse. Like results of the last method, we capture the sign, after that, the nearest neighbour interpolation method is used to resize the image to database models size in fact to enter in the recognition phase and the correlation classification. Even if the previous methods were not able to suppress all original image noise, the small remaining density deforms the ellipse slightly in the direction of the noise location that does not produce an error of the classification. It is necessary to say that two possible sign extractions could be found. In figure 1, the sequence of images are related to input image, Canny contours, noise extraction, radial symmetry, fitted ellipse and sign extraction respectively.

Depending on the obtained contours from the Canny detector, there are two possible sign extractions. The sign could be extracted by the inner contour, in case to have previously lost outer contour segments by confusion of gray levels between sign and background (figure 1 down), or it could be extracted from its outer contour (figure 1 up).



(a) (b) (c) (d) (e) (f)

Figure 1. (a) Original image, (b) Canny contours, (c) Noise extraction, (d) Radial Symmetry, (e) Fitted ellipse, (f) Sign extraction.

In order to check the implemented methods robustness, we designed an image database with 21 circular classes, which representative model is shown in figure 2.

3.2 Designing virtual examples to test the sign recognition process

Each of the 21 different sign classes contains 140 transformations for 10 different angles rotation, with a total of 2940 database images on which we apply 50 image tests. High variance of sign appearance as noise, affine deformation, and reduced illumination has made to increment the database by the generation of virtual samples. The transformations applied for the database set are: gaussian smoothing for different size and sigma values and mathematic morphology operators. The image size chosen in order to maintain the sign characteristics well defined is of 38 by 38 pixels. In figure 3 we see some samples of elements classes and their transformations. By the two possible extractions, we create more elements from each image in order to detect both types. For this task, we included circular signs for each class with edge extractions between 2 and 5 pixels depending on the type of sign. This will allow to fit the correlation between pixels for a successful classification independently on the sign extraction. All elements are normalized by equalization from the gray image levels, and a circular mask is applied to do the correlation only with the representative points of circular signs. Since the input images we used for the test and validation are acquired by a video capture system on noncontrolled surroundings, this performance is proved on real data. We use the k-nearest neighbours algorithm as a classification method. From a simple correlation between the equalized input image resized by nearest neighbour method and the database set, we match each input image by the class that contains most neighbours of the target object. The error parameter between pixels was selected in order to obtain the maximum difference between classes, being 0.15 in a scale between 0 and 1 gray levels. This margin error allows to grant as success the pixels of similar values that correspond to the same class. This fact does not cause classification errors since the equalization emphasizes the changes of intensity in the different sign regions. From the tests we select k=11 nearest neighbors as the experimental value for the classification.

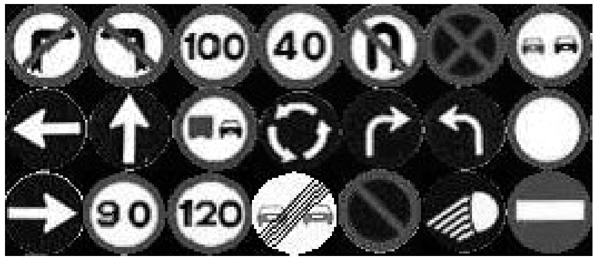
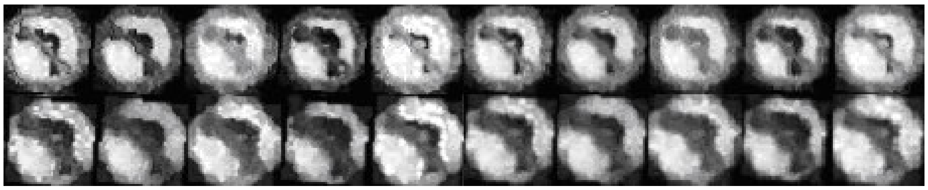


Figure 2. Sign image database.

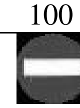


(a) (b) (c) (d) (e) (f) (g) (h) (i) (j)

Figure 3. Different samples from the same sign class. Top images are related to outer contour sign extraction and down images to inner contour sign extraction.
(a) Equalized input, (b) Opening image, (c) Closing image, (d) Eroded image, (e) Dilated image, (f-j) Same transformations for different gaussian parameters.

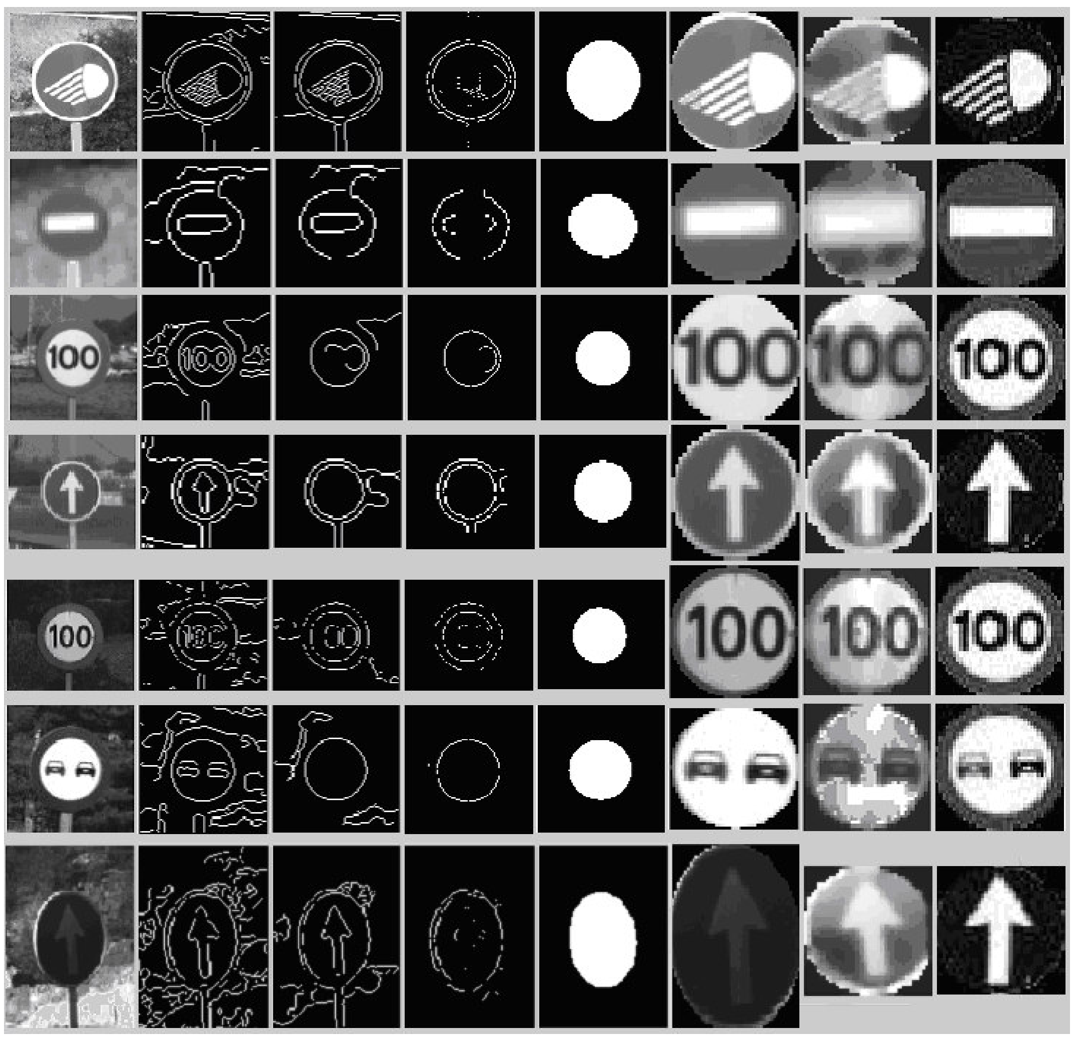
We obtained a 98 % percentage of success from 50 tests performed in order to calculate the method robustness. Five tests were done for each one of the signs of the Table 1, from different input images that contain the sign, to classify on a set of 21 classes. The table percentages are related to each sign classification percentage. We can see that all from the set of 50 tests were correctly classified except the last sign. The sign of the Table 1(j) was the only one not classified correctly. This is due to the great confusion of gray levels between the background and the sign, in addition to being the only circular sign that does not have double border edge. This confusion produces the extraction of all the contours by the application of the first method, considering the sign as a possible false positive incorrectly. In any case, with the Mobile Mapping process there are approximately 3 available frames from the same sign coming from the classifiers cascade. So, the error produced in adverse conditions on a frame is not enough to loss the road sign. The correct results indicate a high robustness of the method in the large set of sign classes we are working with. In addition, the execution time of preprocessing and undistortion since we receive the input is achieved in less than 1 second on a Pentium 4 2,2 GH with 512 MB RAM using MATLAB. In figure 5 we show a set of examples of the complete recognition process.

Table 1 Classification percentage in a set of five tests by sign.

(a)	(b)	(c)	(d)	(e)
100 %	100 %	100 %	100 %	100 %
(f)	(g)	(h)	(i)	(j)
100 %	100 %	100 %	100 %	80 %

3. Conclusions

In this paper we exposed a new fast and simple approach in order to perform model fitting undistortion and recognition for road signs on a grayscale image based upon geometry reasoning. The input is a result of an Adaboost cascade of weak classifiers algorithm, that was previously applied on images acquired in a Geomòbil Mobile Mapping process vehicle. The results show that the presented method offers good robustness in case of high variance of sign appearance as noise, affine deformation, and reduced visibility without need to use color information. At the same time it allows a successful multi-class recognition. In addition, its low time-cost allows to be applied to real-time vision tasks. The road sign detection study is still open. We are currently extending the proposed method to recognize a set of any geometric forms of road signs in order to solve the problem of road sign recognition.



(a) (b) (c) (d) (e) (f) (g) (h)

Figure 5. (a) Original image, (b) Canny contours, (c) Noise extraction, (d) Radial Symmetry, (e) Fitted ellipse, (f) Sign extraction, (g) Normalization and resizing, (h) Classification class.

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References

[1] H. Akatsuka and S. Imai. “Road signposts recognition system.” In *Proc. SAE vehiclehighway infrastructure: safety compatibility*, pages 189–196, 1987.

[2] D. Kellmeyer and H. Zwahlen. “Detection of highway warning signs in natural video images using color image processing and neural networks.” In *IEEE Proc. Int.Conf. Neural Networks 1994*, volume 7, pages 4226–4231, 1994.

[3] M. de Saint Blancard. “Road sign recognition: A study of vision-based decision making for road environment recognition.” In *Vision-based Vehicle Guidance*, Springer Series in Perception Engineering. Springer-Verlag, 1992.

[4] Arturo de la Escalera, Luis E. Moreno, Miguel Ángel Salichs and José María Armingol “Road Traffic Signs Detection and Classification,” *CICYT Project TAP94-0711-C03-02*, jul. 1996.

[5] R. Ghica, S. Lu, and X. Yuan. “Recognition of traffic signs using a multilayer neural network,” In *Proc. Can Conf. on Electrical and Computer Engineering*, 1994.

[6] A. de la Escalera, J.Mª Armingol, M.A. Salich, “TRAFFIC SIGN DETECTION FOR DRIVER SUPPORT SYSTEMS,” *Systems Enginnering and Automation Division*, Universidad Carlos III de Madrid, Leganés, Madrid, Spain.

[7] G. Piccioli, E. D. Michelli, and M. Campani. “A robust method for road sign detection and recognition.” In *Proc. European Conference on Computer Vision 1994*, pages 495–500, 1994.

[8] G. Piccioli, E. D. Michelli, P. Parodi, and M. Campani. “Robust road sign detection and recognition from image sequences.” In *Proc. Intelligent Vehicles’94*, pages 278–283, 1994.

[9] Jordi Vitrià and Xavier Baró, “Traffic Sign Detection on Greyscale image,” *Computer Center Vision*, Spain.

[10] Yoav Freund and Robert E. Schapire. “A decision-theoretic generalization online learning and an application to boosting,” *Computational Learning Theory: Eurocolt* ’95, pages 23-37. Springer-Verlag, 1995.

[11] Paul Viola and Michael J. Jones, “Robust Real-time Object Detection,” *Cambridge Research Laboratory, Technical Report Series*, CRL 2001/01. Feb. 2001.

[12] Gareth Loy and Alexander Zelinsky, “Fast Radial Symmetry for Detecting Points of Interest,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 25, no. 8, Aug. 2003.

[13] Andrew Ditzgibbon, Maurizio Pilu, and Robert B. Fisher, “Direct Least Square Fitting of Ellipses,” *Tern Analysis and Machine Intelligence*, vol. 21, no. 5, may. 1999.

[14] R. Brunelli and T. Poggio, “Face Recognition: Features vs. Templates,” *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol. 15, no. 10, pp. 1,042-1,053, oct. 1993.

[15] Peter N. Belhumeur, Joao P. Hespanha, and David J. Kriegman, “Eigenfaces vs. Fisherfaces: Recognition Using Specific Linear Projection,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 19, no. 7, jul. 1997.

[16] R. Alamús, A.Baron, E.Bosch, J.Casacuberta, J.Miranda, M.Pla, S.Sànchez, A.Serra, J.Talaya, “On the accuray and performance of the GEOMÒBIL system,” *Institut Cartogràfic de Catalunya (ICC), Parc de Montjuïc, E-08038 Barcelona*, Commission II, WG V/2.