Traffic sign shape classification evaluation I: SVM using Distance to Borders

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***Abstract*— This paper deals with the detection and classification of traffic signs in outdoor environments. The information provided by traffic signs on roads is very important for the safety of drivers. However, in these situations the illumination conditions can not be predicted, the position and the orientation of signs in the scene are not known and other objects can block the vision of them. For these reasons we have developed an extensive test set which includes all kind of signs.**
In an artificial vision system, the key to recognize traffic signs is how to detect them and identify their geometric shapes. So, in this work we propose a method that uses a technique based on Support Vector Machines (SVMs) for the classification. The patterns generated by the vectors represent the distances to borders (DtB) of the objects candidate to be traffic signs.
Experimental results show the effectiveness of the proposed method.

I. Introduction

Traffic sign detection and recognition have been an important issue for research recently: [1], [2], [3], [4], [5], [6] are some of these works.
In this introduction a general description of the state of art of segmentation is given and in the introduction of [7] a general overview of the state of the art about shape classification for traffic signs is given.
Basically, the structure of these kind of systems has two stages: one for the detection and one for the recognition. The detection stage is usually based on color segmentation in a given color space. In [8], a ratio of the RGB components is used assuming the red component as reference. In [9], a similar ratio was used where the reference is the sum of the three RGB components. A binarization is performed multiple times using different thresholds in the YUV color space in [10]. In [11], the proper thresholds for Hue and Saturation bands are applied. A non-linear transform over the Hue and Saturation components are applied in [1] and two look-up tables are used for the thresholding. In [12] the input image pixels are classified into two classes: chromatic and achromatic, and then the red rim of circular traffic sign is detected. For the recognition stage many different solutions have been proposed. A Neural Network (NN) is used for the classification following the Adaptive Resonance Theory paradigm in [1]. In [10] the identification of signs is carried out by a normalized correlation-based pattern matching using a traffic sign database. In [13], the proposed sign recognition system consists of a nonlinear correlator. The scene and the reference pattern are both Fourier transformed and nonlinearly modified. The correlation plane between the input and the reference signals is obtained by the inverse Fourier transform. In [14] the recognition is done using matching pursuit (MP) in two processes: training and test. The training process finds a set of best MP filter based for each road sign. The testing process projects the input unknown road sign to different set of MP filter bases to find the best match. The detected sign is normalized and is correlated with all of the prototype in [2], a horizontal and vertical displacement of $\pm$ 3 pixels is allowed. Many of these works show partial solutions to the general problem of traffic sign detection and recognition and none of them show comparative results with other method.
We have created a traffic sign image database test set that can be used to evaluate traffic sign detection and recognition algorithms. Two different methods for detection and classification of traffic signs according to their shape have been developed. The first method is based on Distance to Borders measurement and linear SVM and it is presented in this paper. The other is based on FFT applied to the signature of the blob obtained from segmentation and it is presented in [7].
For these reasons we have developed a test set that covers the most important common problems of traffic sign detection and is available at http://roadanalysis.uah.es. All the signs and properties described are for Spanish traffic signs.

II. Test set categories

In this section we show the different categories we have introduced in the test set.

A. Different shapes

Traffic signs are classified into different shapes. The possible shapes are related to the color of the signs and are the meaning of it. It is necessary to point out that many objects, specially in urban environments, have the same shape and colors than traffic signs and so, they can be confused with the signs. A traffic sign detection system should detect these shapes and, due to different positions where the sign can be found, the module should detect deformed signs because of the projection of the image capture process.

Color	Shape	Meaning
Red Rim	Circle	Prohibition
Red Rim (Up)	Triangle	Danger
Red Rim (Down)	Triangle	Yield
Red	Octagonal	Stop
Blue	Square	Recommendation
Blue	Circle	Obligation
White	Circle	End of prohibition
Yellow	Circle	End of prohibition (construction)

TABLE I

MEANING OF TRAFFIC SIGNS ACCORDING TO THE COLOR AND SHAPE

Fig. 1. Images from category B (Different signs)

B. *Different signs*

Traffic signs give drivers and pedestrians diagrammatic information. If we consider all the information messages, the total number of different signs is quite big. Depending on the computation complexity of the recognition stage, this process could be very slow. Fig. 1 shows some images with different signs.

C. *Different positions*

Our aim is to find a traffic sign detection system invariant to shifts. Nevertheless, some authors reduce the looking zone in order to decrease the computation time. In this category we include some images where the traffic signs do not appear in the usual position. In Fig. 2 some images with different positions in the scene are illustrated.

D. *Rotation*

There are some occasions where, depending on the place where the images are taken, the traffic signs are turned on their transversal or longitudinal axis (see Fig. 3). For this reason, the traffic signs must be recognized and detected even if they are rotated.

E. *Occlusion*

In many situations traffic signs appear partially occluded because there are other elements in the scene such as tree branches, vehicles or other signs that can block the visibility of the signs (see Fig. 4).

Fig. 2. Images from category C (Different positions)

Fig. 3. Images from category D (Different angles of rotation)

Fig. 4. Images from category E (Partially occlusions)

Fig. 5. Images from category F (Different sizes)

Fig. 6. Images from category G (Deteriorated signs)

F. Sign sizes

Since images are captured in motion at different speeds, every traffic sign should appear in different frames or images. So, when the camera approaches to the traffic sign it will appear longer than in the previous image acquired.

G. Deteriorated signs

Sometimes traffic signs present strict deteriorations for various reasons. In fact, this factor can altere their forms and colors, increasing the complexity of the recognition and detection system.

III. System overview

The system that we present in this paper for detection and classification of traffic signs according to their shapes consists of two main stages:

A. Segmentation

Candidate blobs are extracted from the scene by thresholding using Hue and Saturation components for the colored signs. Intensity is not used in order to get an algorithm invariant to changes of illumination. On the other hand, a division in chromatic and achromatic is performed over every pixel using a method similar to the proposed in [12]. The most important advantages of the classification chromatic/achromatic are orientated to the detection of white signs. In this way, we can detect the signs of a cluster individually.
After extracting the candidate blobs, some of these are discarded according to their unsuitable size or aspect ratio regarding to two considerations: a) Irrelevant small blobs and very big blobs are rejected, respectively, like noise and non-interest objects, and b) Since all the signs are regular polygons and, in the ideal position their aspect ratio is , approximately, equal to the unity those blobs whose aspect ratio is much higher or much less than 1 are discarded too, because they may be either noisy blobs or traffic signs with very strong perspective distortion. Finally, each candidate blob in the image is oriented to a reference position in order to get an invariant method against possible rotations.

B. Shape classification

Blobs obtained from the segmentation stage are classified into their shapes. For this purpose we have developed a method based on linear Support Vector Machines (SVMs). SVMs were introduced by Vapnik and an extensive tutorial about it can be found in [15].
In the simplest case the training data can be linearly separated and we label them as $\{\mathbf{x}_i, \mathbf{y}_i\}$,where $i = 1, ..., l$, and $\mathbf{y}_i \in \{\mathbf{R}\}^d$. In our work the vectors $\mathbf{x}_i$ are the distance to borders (DtB) for each blob how we describe later, the values $\mathbf{y}_i$ are '1' for one class and '-1' for the others, d is the number of components of each vector and l is the number of training vectors.
If an hyperplane $\mathbf{w}$ separates the two classes, the points which lie on it satisfy: $\mathbf{w} \cdot \mathbf{x} + b = 0$, where $\mathbf{w}$ is normal to the hyperplane, $|b|/\|\mathbf{w}\|$is the perpendicular distance from the hyperplane to the origin, and $\|\mathbf{w}\|$ is the Euclidean norm of $\mathbf{w}$. For the linearly separable case, the support vector algorithm looks for the separating hyperplane that $\mathbf{w}$ y b should satisfy:

$$\overline{y}_i(\overline{x}_i \cdot \overline{w} + b) - 1 \geq 0 \quad \forall i$$

If we introduce positive Lagrange multipliers a_i, $i = 1, ..., l$, one for each of the inequality constraints (equal to the number of training vectors) the objective is minimize L_p :

$$L_p = \frac{1}{2}\|\overline{w}\|^2 - \sum_{i=1}^{l} \alpha_i \cdot \overline{y}_i(\overline{x}_i \cdot \overline{w} + b) + \sum_{i=1}^{l} \alpha_i$$

Once the optimization is finished, we determine on which side of the hyperplane lies a given test vector $\boldsymbol{x}$ and assign the corresponding label to it. The decision function is given by:

$$f(\overline{x}) = \mathrm{sgn}(\overline{w} \cdot \overline{x} + b)$$

In this work, the vectors that we use as input for the linear SVMs are DtB as it was introduced in [6]. DtB are the distances from the external contour of the blob to the

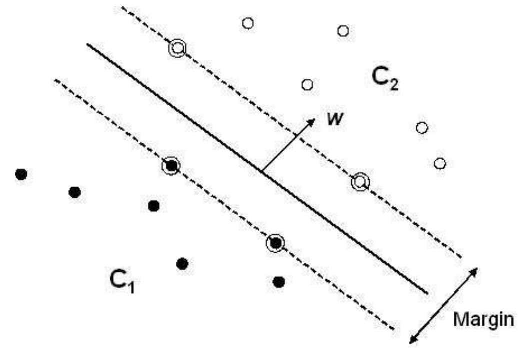


Fig. 7. Linear separating hyperplanes for the separable two dimensional case: class C_1 and class C_2. The support vectors are circled

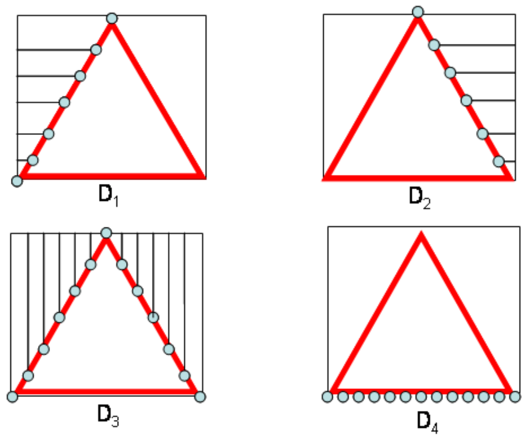


Fig. 8. Extraction of DtB vectors for a triangular shape

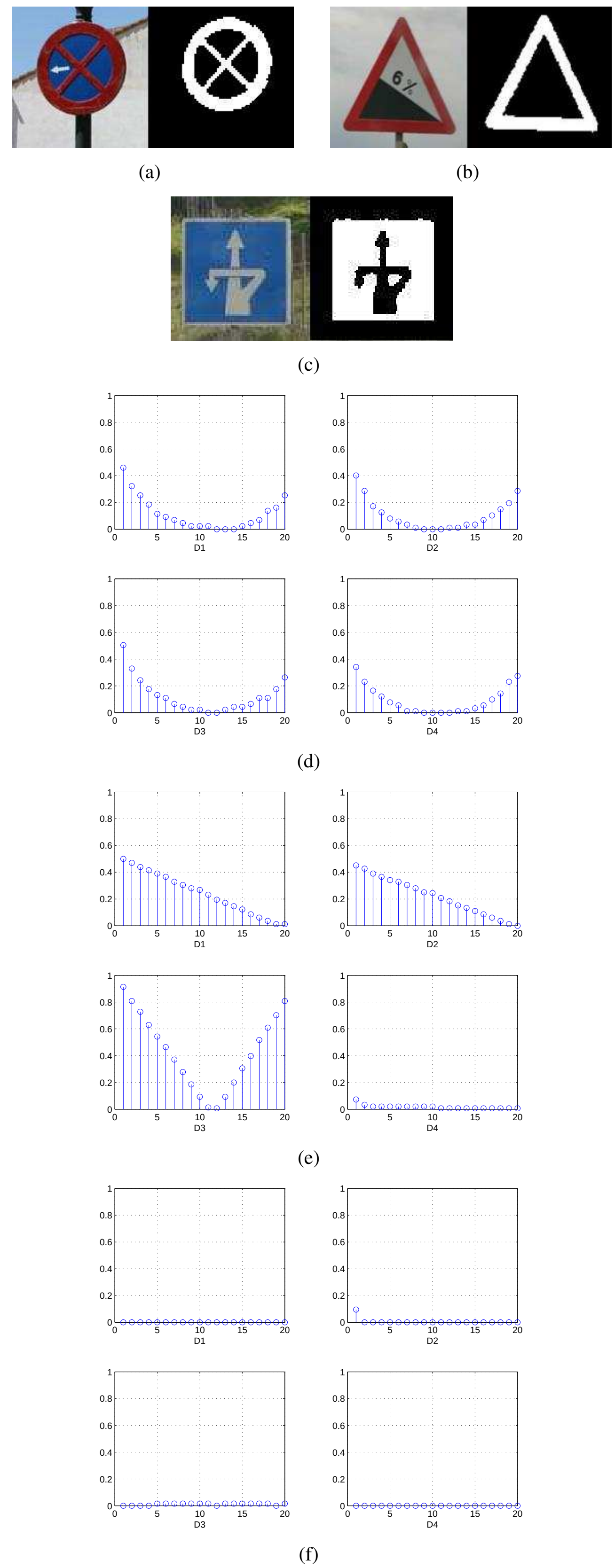
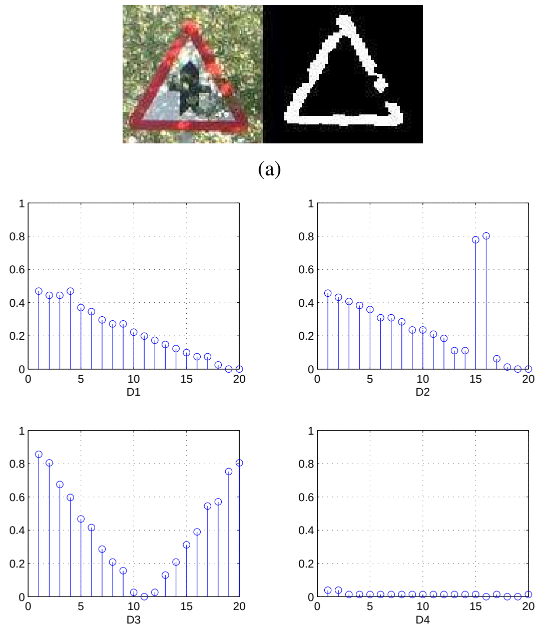


Fig. 9. DtB vectors for traffic signs. (a) Mask of red segmentation for a circular sign, (b) Mask of red segmentation for a triangular sign, (c) Mask of blue segmentation for a rectangular sign, (d) DtB vectors of (a), (e) DtB vectors of (b), (f) DtB Vectors of (c)

bounding-box in which it can be inscribed as we can see in Fig. 8. In the same way, Fig. 9 shows the four DtB vectors for three examples of signs with different shapes.

The main advantage of this method is its robustness to several factors such as translations, rotations and scale. The algorithm is invariant to translation because does not matter where the candidate blobs appear in the scene. It is invariant to rotations because all blobs have been previously orientated in a reference position. And finally, it is invariant to changes of scale because 20 samples equally-spaced of every DtB vector are obtained independently of the size of the traffic signs.
We use a different structure of classifying for each segmentation color. For example, in the case of red segmentated blobs we use eight linear SVMs; four for each possible shape: triangular and circular. Thus, the vectors extracted of a blob by red color feeds four SVMs to classify it as a possible circle (label '1') or no circle (label '-1') and another four SVMs to classify it as a possible triangle (label '1') or no triangle (label '-1'). Then, four favorable votes are possible for each shape and, at least, two votes are required to assign a shape-class to the blobs of interest. A majority voting method has been applied in order to get the classification. In case of tie, positives outputs of SVMs are computed to decide which is



(b)

Fig. 10. DtB vectors for an example of occlusion. (a) Mask of red segmentation, (b) DtB vectors of (a)

the candidate shape and if the total number of votes is lower than 2, the object is discarded like noise.
It is important to point out that octagonal signs are considered like circular because at high-medium distances their vectors are very similar to the corresponding for a circular shape. In the next stage of recognition, stop sign will be identified using the information of its inner area.
In addition to the factors mentioned above, we can say that the method described is strongly robust to occlusions because we describe every geometric shape with four independent parameters. The worst case is when the occlusion blocks the vision of, at least, one of the two points that determine the rotation of the blob. These situations make more difficult the problem of classification with this method because the evolution of DtB vectors can be modified respect to the expected.

IV. Results

The classification algorithm mentioned has been tested using over 300 images approximately of our test set, where one or more traffic signs can be found in each frame.
Table IV shows the results for all categories in the database. The parameters evaluated are: first, the classification success defined as the ratio between the number of signs whose geometric shapes are classified correctly and the total number of signs which have been isolated in the previous segmentation process. The second parameter is the number of false alarms yielded by the system since some segmented noisy blobs of the scene are classified by their shape as possible candidates to traffic signs and the third parameter expresses the loss probability, as the ratio between the number of lost signs (because either they were not correctly isolated in the segmentation process or not correctly classified in the classification step), and the total amount of signs which appear in the images. We note that the most of cases of lost signs are produced because the segmentation of these signs was extremely difficult since other objects of the same color appear next to the sign or the size of signs is quite small when are captured at very high distances from the camera.

For getting these results, the outputs of our system are compared with the position of the sign analyzed by a human operator. From the results summarized in this section we can conclude that our classifying method is very robust for all the problems considered although the number of false alarms caused by the presence of other objects in the scene of similar color and aspect respect to traffic signs is quite high. The loss probability is high specially in the categories of ”Different sizes” and ”Occlusions”. Firstly, in the category of ”Different sizes” there are signs at very high distance from the camera and some of them are not detected by our system and, secondly, in the category of ”Occlusions” some traffic signs have been discarded either by a difficult segmentation mask or because the number of votes at the output of SVMs is lower than the value of the threshold fixed (i.e. 2). However, it is necessary to point out that our system classifies successfully almost all the signs segmented correctly.
An average of 10 signs from a different data set for every shape were chosen for the training process.

Number Imag.	**Category**	**Subcateg.**	**Classif. Success**	**False Alarms**	**Loss Prob. %**
30	Dif. Shapes	Circular	41/41	43	22.23
30	Dif. Shapes	Octagonal	33/34	49	11.2
30	Dif. Shapes	Rectang.	33/35	78	8.11
30	Dif. Shapes	Triangular	61/62	101	28.28
40	Dif. Signs	-	53/54	91	17.25
40	Dif. Posit.	-	73/75	116	26.32
30	Rotation	-	32/32	88	29.27
37	Occlusion	-	45/46	116	47.62
40	Dif. Sizes	-	37/38	74	50.95
23	Deter. Signs	-	42/44	92	25.00

TABLE II

Results for every category

V. Conclusion

This paper proposes a new method for classifying the shapes of traffic signs based on the capability of SVMs. The patterns we use are generated by the four DtB vectors for every sign and, in our aim, we use a linear classification taking advance of its low computational cost.
Experimental results indicate that our system is robust under various conditions. However, the high number of false alarms will be reduced in future works analyzing other measures from blobs than the ones mentioned here. Therefore, in the next stage of recognition noisy blobs will be rejected according to the low similarity between the inner area of traffic signs and candidate blobs.

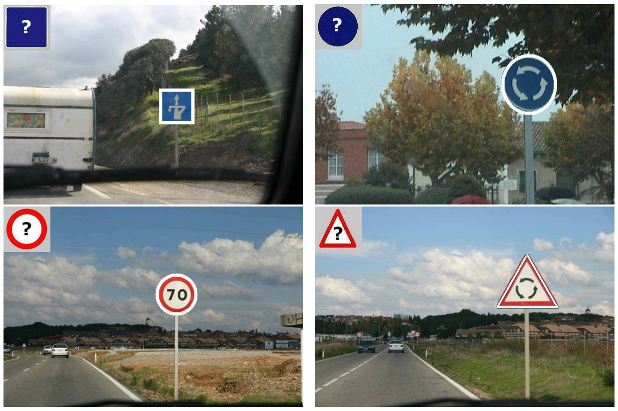


Fig. 11. Traffic sign detection examples using SVMs algorithm

Fig. 12. Traffic sign detection examples with rotations

In this paper only single images are considered. In future works, several consecutive images will be considered and so, using "inter-frame" information, false alarms should be reduced as well as loss probability.
Finally, the specific recognition of every sign has not been studied in this paper and it remains as a future research.

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Fig. 13. Traffic sign detection examples with partially occluded signs

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