MVA'90 IAPR Workshop on Machine Vision Applications Nov. 28-30,1990, Tokyo

USING GEOMETRIC MODEL GUIDED ACTIVE CONTOUR METHOD FOR TRAFFIC SIGN DETECTION

Long QUAN* Roger MOHR**

*CRIN - INRIA Lorraine, B.P. 239, 54506 Vandœuvre-les-Nancy Cedex, France
**LIFIA - IMAG, 46, avenue Felix Viallet, 38031 Grenoble Cedex, France

Abstract

The subject of this paper is on detection, location of traffic signs. The way we are operating is by first detecting salient features, then tracking them, and finally identifying them in a snapshot view at the right resolution. A mixed *model guided active detection* is chosen to compensate for imperfect low level segmentation. The detection is also optimized based on a active contour model. The first experimental results are presented and the future working directions on the topic are also discussed.

1 Introduction

The purpose of our work is to give future drivers a visual assistance. The way we are operating is by first detecting salient features as candidates, then tracking them, and finally identifying them in a snapshot view at the right resolution. A mixed *model guided active detection* is chosen [Kass 88,Poggio 85,Fua 87], since a pure *bottom-up* process has no opportunity for correction and no prior knowledge to be integrated. *Hough transform* (cf. [Duda 72], [Ballard 81], [Illingworth 88] and [Mohr 88]) needs a too large parameter space and is therefore discarded.

Our proposed system can be described as follows:

1. detection and location,
   - possible candidate detection
   - candidate filtering,
   - candidate selection and classification,
   - candidate tracking over time,
   - detection optimization at a given instant,
2. content identification on signs.

In this paper, we are dealing only with candidate detection, filtering, selection, classification and instantaneous detection optimization. However, a brief discussion will be given on the other related points.

2 Candidate detection

First of all, we should model traffic signs. It is a quite easy thing, as traffic signs are in regular normalized geometric forms: triangular, rectangular, octagonal or circular[1]. So generaly, a convex polygon model can be used for triangular, rectangular and octaganal traffic signs and an ellipse can be suitable for a circular one. As it is well known that the convexity is preserved by central projection, A convex edge chain gives a good traffic sign candidate. Techniques are available for edge detection and chaining. It remains only how to get right convex chains.

Candidate detection begins with a classical edge detection and followed by an edge linking algorithm (cf. [Deriche 87, Giraudon 87]). Then we decompose these edge chains into convex sub-chains. First, a polygonal approximation is applied to the obtained edge chains. It acts also like a smoothing effect on edge points. We are currently using a linear time consuming algorithm proposed by Wall and Danielsson [Wall 84] to do so. A chain is said to be convex if the completed polygon by the missing segment gives always a convex hull. It is obvious that a linear scanning of linked segments of a chain is sufficient to break up it into convex sub-chains. This can be illustrated by Figure 1. *Each convex sub-chain is thus considered as a possible candidate for the time being.*

Figure 1: Decomposition of a chain into convex sub-chains.

[1]Actually we are particularly interested in triangular and circular signs.

Figure 2: Traffic signs candidates.

3 Candidate selection

So far, a great amount of candidates is obtained by the previous processing. They are too numerous to manipulate. We have to choose the good candidates and then classify them. So what is a good candidate? Obviously we are not interested in a highly elongated chain on one direction. We prefer more radially symmetric chains. This suggests that *compactness* of a chain is a good selection criterion. As we known that the compactness is defined by the ratio of the area of the curve over the perimeter square of the chain, i.e. $compactness = (area)/(perimeter)^2$. This is a scale-invariant number characterizing the curve. For all possible curves it is maximized by the most compact one, a circle. By most compact, we mean most radially symmetric. This permit us to eliminate all non compact enough convex chains.

Chromatic information should be exploited, since traffic signs are chromatically normalized. From original tristimuli R, G, B images (cf. [Pratt 78]), we can calculate the intensity image I by $R + G + B/3$, this intensity image can be analyzed as a normal B/W image, especially to get possible candidates as we did above. Color information is added around through color binary images. Red binary image is calculated by logical operators between R, G, B images:

$$R > G \text{ and } R > B.$$

Intuitively it means that a real red object should be most sensed in the red band. Similarly, we can compute the green (respectively blue) binary image by $G > R$ *and* $G > B$ (respectively $B > R$ *and* $B > G$). After these, a morphological operator *Opening* (cf. [Serra 82]) can be applied to each color binary image to get rid of small isolated particles. These color binary images can then be used to further select candidates. To do it, a specific color binary image is superimposed with the corresponding intensity image. For each previously selected candidate convex chain, if its enclosed area and a colorful region are overlapped, it will be confirmed, else it will be eliminated.

Figure 2 displays *good* candidates, each one is inscribed in a rectangle.

Figure 3: First candidate classification test

4 Candidate classification

Now we are trying to give a first classification of selected candidates. This is done by fitting a selected candidate to a given geometric model (a triangle or a rectangle or an ellipse). The classification criterion is thus the *goodness of fitting* of the chain. That is, if a chain fits better to an ellipse than a polygon, it will be classified as a circular sign. The fitting criterion is the usual *least squares fitting*. That is, Fitting n points (x_i, y_i) $i = 1, \dots n$, to a model which has m adjustable parameters $a_1, \dots, a_m$: $y(x) = y(x; a_1, \dots a_m)$ i.e.

$$minimize\ over\ (a_1 \dots a_m):$$

$$J(a_1 \dots a_m) = \sum_{i=1}^{n} \sigma_i(x_i, y_i, a_1 \dots a_m).$$

where

$$\sigma_i(x_i, y_i, a_1 \dots a_m) = (y_i - y(x_i; a_1 \dots a_m))^2.$$

As for best polygon fitting for a triangular or a rectangular sign, it is just the well known classical line fitting problem. However, to best fit an ellipse, it is in general case a complex nonlinear problem. We have to use a numerical minimization procedure to do it. Generaly, it requires five parameters to define an arbitrary ellipse: its center, major and minor axes and its orientation. In our case, since it is impossible to have a rotated ellipse, the number of parameters can be reduced to four instead of five. Suppose that the ellipse center is (x_0, y_0) and a and b are respectively its major and minor axis, we have fitting equation $f(x, y; x_0, y_0, a, b) = b^2(x - x_0)^2 + a^2(y - y_0)^2 - 1$. However the error function directly defined by this equation does not give satisfactory fitting. We take the error function that is averaged by its gradient. Then a conjugate direction method is used to get best ellipse fitting. The related work on fitting conic curves can be also found in [Agin 81,Landau 87,Negata 85,Ponce 89,Pavlidis 82].

Figures 3 and 4 show this first classification. A circular candidate is displayed by an ellipse and a polygonal candidate is displayed by a polygon.

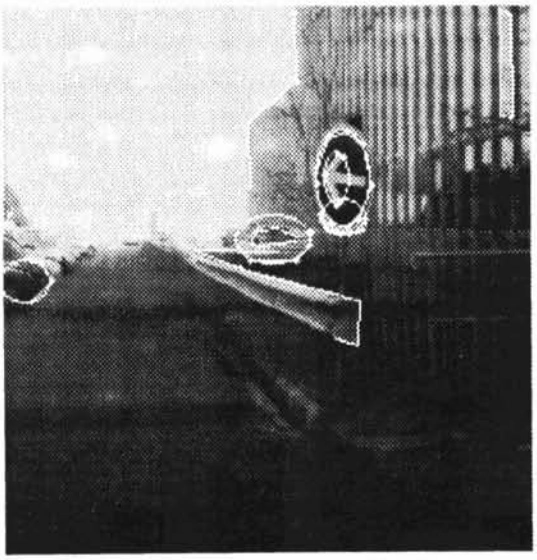

Figure 4: Second candidate classification test

Figure 5: Detection optimization

5 Detection optimization

After the classification, we are going to perform detection optimization which permit us to better locate the traffic sign in the image and to further confirm the classification.

The principle is the generalized active contour idea of *Snake* [Kass 88] which is also successfully used by Fua [Fua 89] in aerial image analysis.

The contour of an object is characterized by an objective function. This function includes both the photometric and geometric model of the object. A pure snake is an energy minimizing spline influenced by the image force. The objective function is

$$F = \int_C - \| \nabla I(x_i, y_i) \|^2 dt + \int_C (\alpha \|C'\|^2 + \beta \|C''\|^2) dt.$$

Therefore the photometric model is the gradient field of the image and the geometric models are just smooth spline curves.

In our case, the objective function is only image gradient force:

$$F = \int_C - \| \nabla I(x_i, y_i) \|^2 dt$$

The geometric model is not directly included in the function, but it will be imposed *explicitly* in optimization step.

The optimization procedure is an iterative gradient method.

1. compute the gradient of the objective function
$$\nabla F = (\frac{\partial F}{\partial X}, \frac{\partial F}{\partial X}).$$
2. deform the curve in the gradient direction with a step λ,
$$(X_{n+1}, Y_{n+1}) = (X_n, Y_n) + \lambda \frac{\nabla F}{\| \nabla F \|}.$$
3. fit geometric model with least-squares technique
4. update the curve for the next iteration

The procedure stops until the curve is stable.

Figure 5 shows this optimization step.

6 Discussion

We proposed an active detection of traffic signs in this paper. Candidate detecting is performed by first an edge detection and then edge linking. The edge chains are then broken up into convex sub-chains as possible candidates. This list of candidates is filtered by the local geometric properties *compactness* and chromatic information to get the *good* candidates. The principle of detection is formalized in termes of an optimization problem, inspired by the Fua's application in areal imagery analysis. The objective function to optimize in our case is the energy created by gradient image, which is then optimized under constraints provided by objects geometric models. This geometric optimization is in its turn considered as a least-square fitting problem.

The strong points of this method are basically as following:

- The detection is guided by geometric models, thus it permits to reward for a poor edge detection in some extent. It is therefore a robust approach.
- Location is optimized, therefore traffic signs are quite accurately located.
- Tracking over time is straight forward. Since the detection in the current frame gives a good starting position for the active detection in the next frame. Of course this is possible only when frames are close enough. If not, we have to integrate the available motion information of the vehicle.
- The numerical behaviour of the optimization step is more stable than the pure Snake convergence.

The main weak point of the method remains principally in the fact that the ellipse nonlinear fitting is quite time consuming in its actual implementation.

Future work is actually directed toward temporal tracking for integrating available motion information.

References

[Agin 81] G.J. Agin. Fitting Ellipses and General Second-Order Curves. *CMU-RI-TR-81-5*, 1981.

[Ballard 81] D.H. Ballard. Generalizing the Hough Transform to Detect Arbitrary Shapes. *Pattern Recognition*, 13(2):111–122, 1981.

[Deriche 87] R. Deriche and J.P. Cocquerez. Connected Components Labeling Based on Optimal Edge Detection. In *Proc. COGNITIVA87*, pages 1–7, Paris, 1987.

[Duda 72] R.O. Duda and P.E. Hart. Use of the Hough transform to detect lines and curves in pictures. *Communication of ACM*, 15():11–15, 1972.

[Fua 87] P. Fua and A.J. Hanson. Using Generic Geometric Models for Intelligent Shape Extraction. In *Proc. AAAI87 Conference*, pages 706–711, Seattle, WA USA, 1987.

[Fua 89] P. Fua and A. Hanson. Objective Functions for Feature Discrimination: Applications to semi automated Feature Extraction. In *Proceedings of the DARPA Image Understanding Worshop*, Detroit, USA, may 1989.

[Giraudon 87] G. Giraudon. *Chaînage efficace de contour.* Rapports de Recherche 605, INRIA, Rocquencourt, France, 1987.

[Illingworth 88] J. Illingworth and J. Kittler. A Survey of the Hough Transform. *Computer Vision Graphics and Image Processing*, (44):87–116, 1988.

[Kass 88] M. Kass, A. Witkin, and D. Terzopoulos. Snakes: Active Contour Models. *International Journal of Computer Vision*, ():321–331, 1988.

[Landau 87] U.M. Landau. Estimation of a Circular Arc Center and Its Radius. *CVGIP*. 1987.

[Mohr 88] Roger Mohr, Long Quan, and Eric Thirion. Feature grouping : a way to deterministic matching. In *Proc. of the Workshop on Syntactical and Structural Pattern Recognition*, pages 213–227, Pont-à-Mousson, France, 1988.

[Negata 85] T. Negata. Detection of an Ellipse by Use of a Recursive Least-Squares Estimator. *Journal of Robotic Systems*, 2(2):163–177, 1985.

[Pavlidis 82] T. Pavlidis. Curve Fitting as a Pattern Recognition Problem. In *Proc. ICPR*, pages 853–859, Munich, 1982.

[Poggio 85] Tomaso Poggio, Vincent Torre, and Christof Koch. Computational Vision and Regularization Theory. *Nature*, 1985.

[Ponce 89] J. Ponce and D.J. Kriegman. On Recognizing and Positioning Curved 3D Objects from Image Contours. In *Appeared in the 1989 DARPA Image Understanding Workshop*, 1989.

[Pratt 78] W.K. Pratt. *Digital Image Processing.* Wiley-Interscience, New York, 1978.

[Serra 82] J. Serra. *Image Analysis and Mathematical Morphology.* London, 1982.

[Wall 84] K. Wall and P. Danielsson. A Fast Sequential Method for Polygonal Approximation of Digitized Curves. *Computer Vision, Graphics and Image Processing*, 28:220–227, 1984.

Acknowledgements

This work has been funded by MRT (French Ministry of Research and Technology) under European project EUREKA — PROMETHEUS. We would like to thank PSA for providing us with necessary images.