Multi-resolution Image Analysis for Vehicle Detection

Cristina Hilario, Juan Manuel Collado,
José Maria Armingol, and Arturo de la Escalera

Grupo de Sistemas Inteligentes, Universidad Carlos III de Madrid
C/ Butarque 15, 28911 Leganés, Spain
{chilario,jcollado,armingol,escalera}@ing.uc3m.es

Abstract. Computer Vision can provide a great deal of assistance to Intelligent Vehicles. In this paper an Advanced Driver Assistance Systems for Vehicle Detection is presented. A geometric model of the vehicle is defined where its energy function includes information of the shape and symmetry of the vehicle and the shadow it produces. A genetic algorithm finds the optimum parameter values. As the algorithm receives information from a road detection module some geometric restrictions can be applied. A multi-resolution approach is used to speed up the algorithm and work in realtime. Examples of real images are shown to validate the algorithm.

1 Advanced Driver Assistance Systems

1.1 Motivation

Several Advanced Driver Assistance Systems (ADAS), that nowadays are being researched for Intelligent Vehicles, are based on Computer Vision [1]. One of them has the goal of detecting and tracking other vehicles. Present day, commercial equipments are based on distance sensors like radar or laser. These sensors have the advantage of giving a direct distance measurement and, above all, they are able to work under bad weather conditions. Their main inconvenience is the field of view, which is very narrow, so they can only detect the vehicle in front of the sensor. If the vehicle is overtaken, there is a step input to the system and the response can be unstable. One alternative or complementary sensor is vision. Although it is not able to work under bad weather conditions and its information is much difficult to process, it gives a richer description of the environment that surrounds the vehicle. Besides, many of the current traffic accidents happen under good weather and are due to human errors.

1.2 Previous Work

The research on vehicle detection based on an onboard computer vision system can be classified in three groups:

- Bottom-up. There are some features that define a vehicle (symmetry, edges, shadow), and they are looked for sequentially in the image. Their main inconveniences are: the vehicle is lost if one feature is not present enough in the image and false tracks can deceive the algorithm.

- Top-down. There are one or several models of vehicles and the best model is found in the image through a likelihood function. They are more robust than the previous algorithms, but slower. The algorithm presented in this article follows this approach.
- Learning based. Mainly, they are based on neural networks. Many images are needed to train the network. They are usually used in conjunction with a bottom-up algorithm to check if a vehicle has been actually detected. Otherwise, they have to scan the whole image and they are very slow

The shadow under the vehicles is looked for in [2]. To do so, a sample of the road just in front of the vehicle is taken and darker zones are searched. For these regions, symmetry and vertical edges confirm if there is a vehicle. A similar approach is found in [3]. In [4] a formula for symmetry is proposed. An elastic net is placed at the maximum and it is deformed until the vehicle is found. Interesting zones in the image are localized in [5] using Local Orientation Coding. A Back-propagation neural network confirms or rejects the presence of a vehicle. [6] follows the previous work but adding texture and shadows. The tracking is done using the Hausdorff distance to a model. Another example of fusing shadow, entropy and symmetry is found in [7]. In [8], shadows and symmetry are proposed to localize interesting zones; a neural network confirms the hypothesis. Symmetry is used in [9] to determine the column of the image where the vehicle is. After that, they look for an U-form pattern to find the vehicle. The tracking is performed with SSD correlation. They use a multi-resolution approach. Edges and symmetry are also used in [10]. In [11] overtaking vehicles are detected through motion (image difference) and the other vehicles through correlation. The dimension of the correlation window is calculated through edge detection. Several 3D models of vehicles are used in [12]. The road limits are calculated and the geometrical relationship between the camera and the road is known. Preceding vehicles are detected in [13]. They calculate a Multiclustered Modified Quadratic Discriminant Function through examples, and look for vehicles in regions of 16x16 pixels in the image.

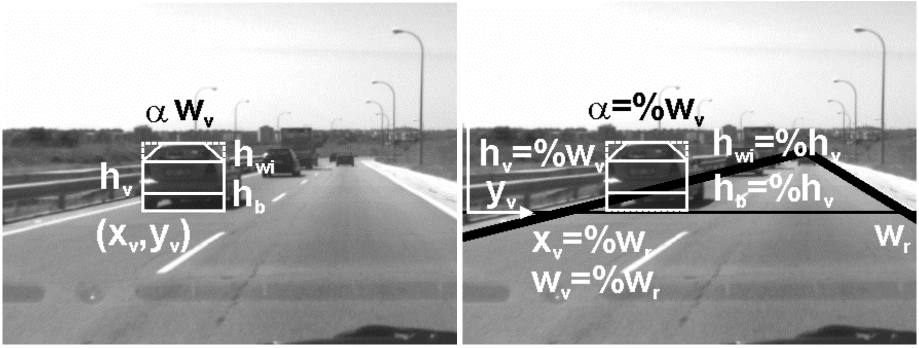
2 Geometrical Models

As stated in [14], a global shaped model based image segmentation scheme consists of the following blocks:

- The initial model, M.
- The deformable model $M(Z)$. This model is obtained from the previous one through the deformation parameters, Z.
- The likelihood probability density function, $P(I|Z)$, which means the probability of the deformation set Z occurs, in the image I.
- A search algorithm to find the maximum of the posterior probability $P(Z|I)$.
- The likelihood function $P(I|Z)$ has to be designed to reach its maximum value when the deformed model matches image I.

2.1 Geometrical Model of a Vehicle

Due to shadows, occlusions, weather conditions, etc, the model has to incorporate as much information as possible. In this paper, a vehicle is defined by seven parameters



(a) (b)

Fig. 1. Geometrical model of a vehicle. (a) A vehicle is defined by seven parameters: Position (x,y), width and height of the vehicle, windshield position, bumper position and roof angle (b) The values of this parameters are constrained by the detection of the road.

(Fig. 1-a): Position (x,y), width and height of the vehicle, windshield position, bumper position and roof angle. In a previous research, [15], the seven parameters had a range but, while the range of the X and Y position, and the width and height of the vehicle were in pixels, the range of the windshield and bumper position and the roof angle were a percentage of the height or width.

A previous detection of the road limits is done in [2] [10]. This can help the vehicle detection step because the searched area is smaller. In the present case, both borders of the road are found and modelled by equations:

$$x = f_l(y) \quad x = f_r(y) \tag{1}$$

that are the slope of the straight lines in this case, but the algorithm would be the same if they were parabolas or clotoids. For a specific y_v value (Fig. 1-b), the width of the road is found:

$$x_l = f_l(y_v) \quad x_r = f_r(y_v) \Rightarrow w_r = x_r - x_l \tag{2}$$

The x_v value of the vehicle and its width are two percentages of the width of the road:

$$x_v = K_x w_r \quad w_v = K_w w_r \tag{3}$$

The height of the vehicle is proportional to the width:

$$h_v = K_h w_v \tag{4}$$

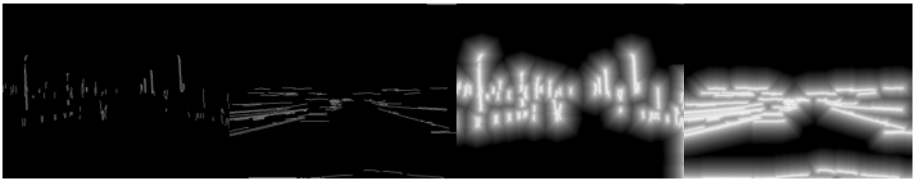
And finally, the windshield and bumper position and the roof angle are a percentage of the height or width.

$$h_{wi} = K_{wi} h_v \quad h_b = K_b h_v \quad \alpha = K_\alpha w_v \tag{5}$$

Then, the deformation parameter vector is:

$$Z = \{y_v, K_x, K_w, K_h, K_{wi}, K_b, K_\alpha\} \tag{6}$$

(a) (b)



(c) (d)

Fig. 2. Image processing (a) Image (b) Vertical and horizontal gradients (c) Vertical and horizontal edges (d) vertical and horizontal distances

2.2 Energy Function

The energy function considers the following three factors: Symmetry, shape and the vehicle shadow (Fig. 2).

Symmetry

The symmetry of the vertical and horizontal edges is considered. For this reason, the vertical and horizontal gradient components of the image are found (Fig. 2-b, Fig. 2-c). Only the pixels with a high response in one of the components and low in the other are taken into account. Then, the pairs of pixels in the same line vote for the central pixel as their symmetry axe. The formulae can be found in [15].

Shape

Shape is defined by two energy terms: one based on the gradient (Fig. 2-b) and the other one based on the distance to the edges, found before for the symmetry energy (Fig. 2-d). The formulae can be found in [15]. Here, only the distance formula is explained, because it has changed from the previous research. A distance image is obtained where each pixel shows the distance to the nearest edge. In order to emphasized the pixels that are near to the edges, the following look up table is applied

$$Lut(D) = \begin{cases} 255(1 - sqrt(D/D_{\max})) & 0 < D < D_{\max} \\ 0 & D > D_{\max} \end{cases} . \tag{7}$$

From that image, a distance to vertical edge energy, D_{GV}, and horizontal edge energy, D_{GH}, are calculated, where D_G is the global distance energy.

$$D_{GV} = \frac{1}{2h}\left(\sum_{j=y}^{y+h} Dv(x, j) + \sum_{j=y}^{y+h} Dv(x+w, j) \right) \tag{8}$$

$$D_{GH} = \frac{1}{4w}\left(\sum_{i=x}^{x+w} Dh(i,y) + \sum_{i=x}^{x+w} Dh(i,y+t) + \sum_{i=x}^{x+w} Dh(i,y+m) + \sum_{i=x}^{x+w} Dh(i,y+h) \right) \quad (9)$$

$$D_G = \frac{(D_{GV} + D_{GH})}{2}. \quad (10)$$

Shadow

The shadow energy, E_{SOM}, of a vehicle with height h, width w, position (x,y), and bumper position m, is defined by the average level of grey in the lower part of the model. Again, the formulae can be found in [15].

Global Energy

The final energy, E, is:

$$E(Z) = -(k_A E_{Sim}(Z) + k_B E_G(Z) + k_C E_D(Z) + k_D E_{Som}(Z)) \quad (11)$$

where k_A, k_B, k_C and k_D allow a weighted sum of the energy terms.

2.3 Likelihood Probability Density Function

The estimate of a given deformation Z for the image I, $P(I|Z)$, follows a Gibbs distribution [14]:

$$P(I \mid Z) = \frac{1}{K} \exp - E(Z) \quad (12)$$

where K is the normalizing constant.

The detection problem is the search of the Maximum A Posteriori (MAP) estimation of Z.

$$Z_{MAP} \in \arg\max_{Z} P(I \mid Z) \in \arg\min_{Z} E(Z) \quad (13)$$

The energy function is minimal when the deformed model exactly matches with the one presented in the image.

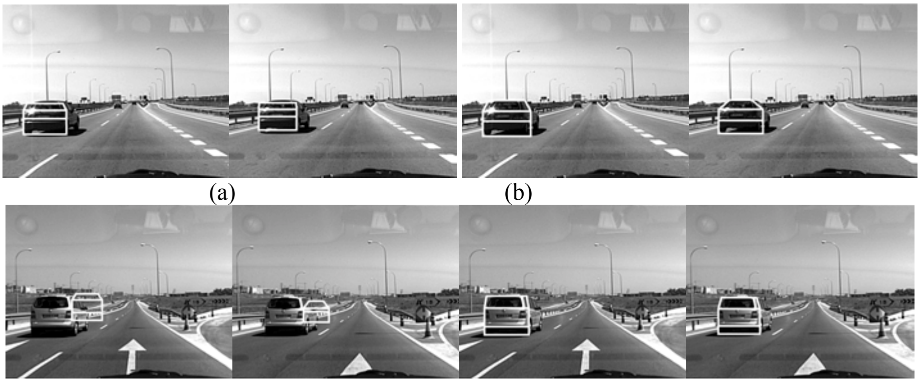
2.4 Search Algorithm

Search algorithms have to find a balance between two opposite tasks: exploration of the complete search space and the exploitation of certain zones. With exploration, the search space is covered looking for promising areas in which a more detailed search has to be done; that is the exploitation task, where the best solution is looked for in a zone known as suitable. The risk is being trapped in a local maximum or minimum. Hashing methods are the extreme case of exploration, where gradient-based methods (hillclimbing) are the extreme for exploitation.

Genetic algorithms (GAs) [16] do a parallel search in several directions following an optimisation process, which imitates natural selection and evolution. To accomplish this task, there is a set of possible solutions (the individuals) that exchange information depending on the fitness of the result in the search for the global maximum. GAs robustness relies in their ability to reach a global maximum surrounded by local ones.

(a) (b) (c)

Fig. 3. Multi-resolution detection at (a) 160x120 (b) 320x240 (c) 640x480 pixels



(a) (b)

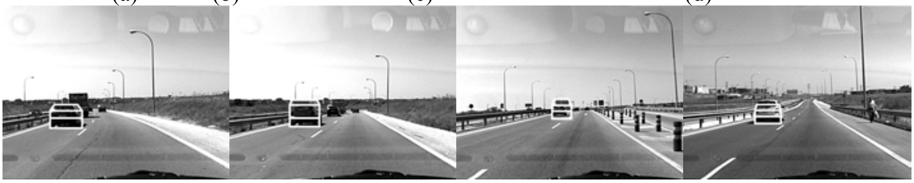
(c) (d)

Fig. 4. Advantages of a multi-resolution approach. (a) small errors in the vehicle detection (b) multi-resolution detection (c) wrong detection (d) multi-resolution detection

3 Results

The detection of the vehicle is done for multiple resolutions. A Gaussian pyramid is built, with dimensions: 160x120, 320x240, and 640x480 pixels. The information of the detection of lower levels is passed to greater levels (Fig.3). Working with a multi-resolution approach has the main advantage of working with the best resolution for every circumstance. Take for example Fig. 4-a. The vehicle has been detected but, as there are many edges inside the car, there are some small errors in the detection. Those edges inside the car have less importance at a lower resolution and the detection is better (Fig. 4-b). But, not only it is useful to improve the results but also to detect successfully a vehicle. As the vehicle is in a cluttered environment, some edges in the environment can deceive the algorithm if an image with great detail is used (Fig. 4-c). Again, working first with a smaller image improves the results (Fig. 4-d).
Another advantage is the saving in computational time. In [15] 550 individuals were needed to detect the vehicles in front of the camera. With the present approach, only 32 individuals are needed. That means the algorithm spends now an average time for a genetic generation of 0.16 ms instead of the 24ms of [15] (in a Pentium 4 Mobile at 1.7 GHz). The other parameters of the GA algorithm are:

(a) (b) (c) (d)



(e) (f) (g) (h)

Fig. 5. Some results and errors. (a)-(e) Successful detection of vehicles. (f)(g) Other rectangular objects are taken as part of the vehicle (h) an inner part of the vehicle is taken.

- Crossover probability: 70%
- Mutation probability: 3%
- Elitism

More results are shown, from Fig. 5-a to Fig. 5-e. Some errors are also shown. In Fig. 5-f-g, the vehicle detected is taller than the real one. This is because some rectangular objects in the environment, like buildings or informative signs are taking as part of the vehicle. Also, when the vehicle is very close to the camera, a smaller vehicle is detected (Fig. 5-h).

4 Conclusions

A system based on computer vision for the detection of other vehicles has been presented in this paper. It is based on a geometric model and its energy function includes information of the shape and symmetry of the vehicle and the shadow it produces. A genetic algorithm has been used to find the optimum parameter values. The algorithm is able to detect vehicles in front of the camera, and it can also detect lateral vehicles and trucks.

Acknowledgments

This work was supported in part by the Spanish CICYT Grant TRA2004-07441-C03-01.

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