Road Segmentation and Obstacle Detection by a Fast Watershed Transformation

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Abstract

This paper presents the work, performed at CMM as part of the European PROMETHEUS project, concerning road / lane segmentation and obstacle detection in a dynamic scene. Road / lane segmentation is used to select ROI where obstacle detection algorithms are applied. This segmentation is made up of a temporal filter, an edge detector and a watershed transformation. It produces a marker of the current traffic lane. This marker is then used for calculating a road model which is continuously updated. The obstacle detection uses various criteria: existence of a darker region marking a vehicle, size and contrast of obstacles and symmetry.
These two processes use the watershed transformation which is usually the slowest part of the segmentation. To speed it up, a very efficient enhancement of the algorithm, based on anamorphosis, is presented.

1. Introduction

The Center of Mathematical Morphology is involved in the European PROMETHEUS project with other French research laboratories and with the car manufacturers PSA and Renault for designing a car demonstrator named Prolab2. This demonstrator is equipped with various video cameras (two front view cameras, one rear view and two lateral cameras). One of the front view cameras is coupled with a telemeter. In addition to these sensors, two CCD linear cameras are used for stereovision. Our participation in this demonstrator is the development of a real-time, on-board image processor for analyzing images provided either by one of the front cameras or by the rear one. The result of the image processing consists of a list of obstacles in front of or behind the car. The position and estimated distance of each obstacle is given to a supervisor which then delivers messages and warnings to the driver through a man-machine interface. This information is particularly helpful in the case of the rear view camera where no telemeter is available for contributing to the distance measurements.
Two main tasks are performed by the image processor. The first one is the segmentation of the road and of the traffic lanes. This task is a background task performed continuously by the processor. The second one is the obstacle detection. This task may be either a background task (information is sent permanently) or a task performed on request by the supervisor.
This paper is not devoted to an in-depth description of the algorithms used for achieving these tasks. An in-depth review of the morphological tools used in this project can be found in [3], [5], [6], [11] and [12]. We simply emphasize the different adjustments and modifications which have been performed for increasing the speed of the algorithms without reducing too much their efficiency and robustness. Special hardware has been designed for performing the obstacle detection and lane segmentation in real time [7], [8]. This hardware is based on a SIMD-NP architecture built with a mathematical morphology ASIC named PIMM1 [9]. Among the various morphological tools used, the most important is the watershed transformation [1]. Although it is a very efficient tool for segmentation, it is also time consuming. Recent algorithms using FIFO and hierarchical queues (HQ) speed up the watershed [4]. Unfortunately, there is still no hardware implementation of these HQ algorithms and they cannot be applied to a SIMD-NP architecture. So, another approach has been used to speed up the watershed. This approach is based on the use of classical morphological transforms suitable for a SIMD architecture, coupled with an anamorphosis to reduce the number of processed gray levels in the image.

2. Road and lane segmentation

The first task is devoted to the segmentation of the road and of the traffic lanes.

Purpose of the segmentation

The purpose of the road and lane segmentation is not at first sight obvious. In fact, this part of the process is of major importance for the following reasons:

- Its provides useful information on the car position with respect to the lane boundaries. Moreover, the nature of the ground marking can be analyzed, with as a final result, an increase of the driver's safety.
- It allows us to compute the coordinates of the regions of interest in the scene and in particular those of the windows where the obstacle detection algorithm is applied. The selection of regions for obstacle detection has many advantages: the size of the image to be processed is reduced and consequently the computation time. Moreover, the detected road or lanes can be used as a template for rejecting artifacts or false alarms produced by the obstacle detection task. Finally when the obstacle detection is performed on request, this process can be easily focused on a particular lane.
- The detection of the lane boundaries also provides the dynamic parameters (magnification factors) allowing the calculation of the 3D real coordinates of objects on the road from their 2D position in the image. These parameters must be continuously updated. If x_e and y_e are the coordinates in the image of a point on the road, the corresponding coordinates (x,y) in the real world (the coordinates axes are drawn at Figure 1) are given by:

$$x = \frac{R|y_F|(D^2+y_e y_F)}{D(D^2+y_F^2)^{1/2}(y_e-y_F)}$$

$$y = \frac{R y_e y_F}{D(y_F-y_e)}$$

where D is a magnification factor depending on the optical system and R a parameter which can be derived from the 2D equations of the lane boundaries. y_F is the line coordinate in the image of the vanishing point of the scene.

Lane segmentation algorithms

Two lane segmentation algorithms are used. The first one is used during the initialization step and performs a first extraction of the current traffic lane from scratch. The second one is activated in the steady state and uses the previous segmentation to match a computed model of the lane with the next image. This model produces a new segmentation which, in turn, is used to update the road model. Both processes use the same main steps and the same morphological segmentation tool: the watershed transformation. These main steps are the following:

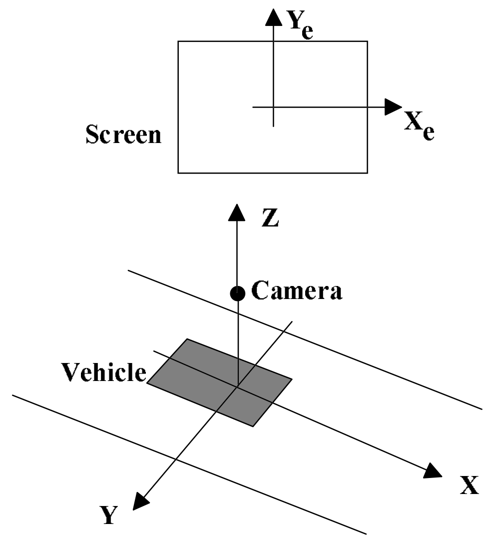

Figure 1: Image and real world coordinates

Figure 2: Connection of the ground marking by a temporal filter: original image (up), filtered image (down)

- A morphological temporal filter [10] is applied over a number of successive images to remove noise and to close the white discontinuous (if any) ground marking. The number of successive images is determined by the speed of the car and by the acquisition rate. Although a temporal alternate sequential filter would be recommended, in order to reduce the computation time, a simple temporal dilation is used in practice. Moreover, the size of this dilation (that is, the number of successive images) is lower during the steady state segmentation (tracking mode) than it is during the initial step (acquisition mode). This variation of size leads to a better management of the changes of lane during the tracking mode. On the other hand, the acquisition mode needs a larger size of temporal dilation and consequently can only be done when there is no vehicle in the fore-ground (Figure 2).
- An edge detector made of a combination of a morphological gradient and of a top-hat transform is then applied to the previous image.

Figure 3: Watershed of the gradient of the filtered image

- Finally, a watershed transformation of the gradient image is performed. This watershed transformation is slightly different depending on its use during the acquisition mode or during the tracking mode. In the former case, a simple watershed is performed. Provided that the temporal filter is sufficiently efficient, a simple catchment basin marks the current lane (Figure 3). Its right and left boundaries can then be used to compute a lane model (a straight lane model is used in practice). In the latter case, the previous lane model is used to build a marker of the lane which is injected to the watershed transform of the next image. Then this new watershed produces a simple catchment basin fitted to the new lane image. Then a new lane model is calculated and the entire process can be run again on the following image (Figure 4).

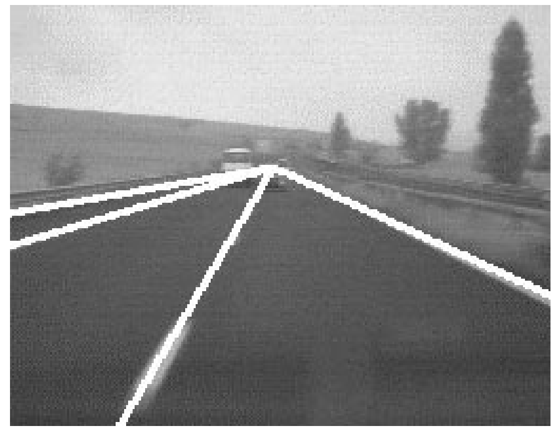

Figure 4: Segmentation in tracking mode (rear view)

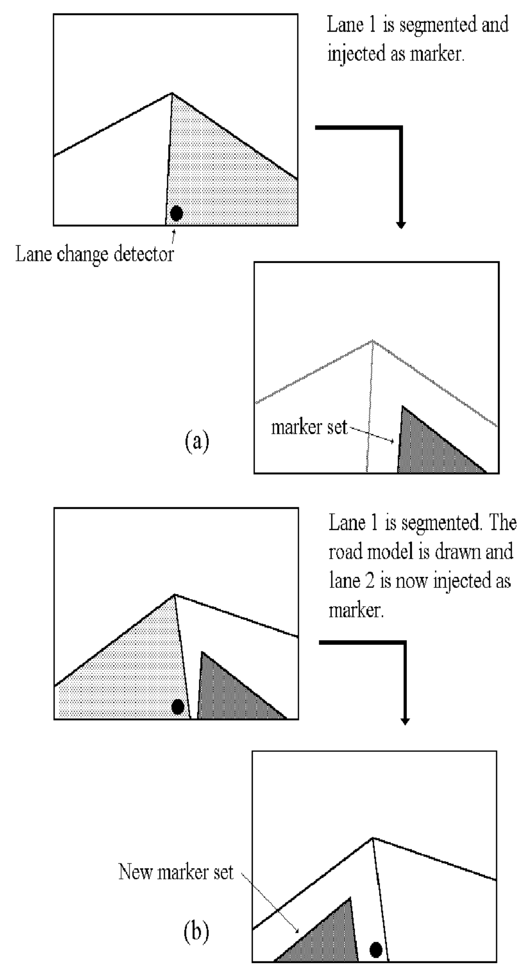

Figure 5: Change of lane and selection of a new marker from the road model - (a) time n, (b) time n+1

Moreover, if the number of lanes and the initial position of the car are known (these data can be entered manually), the change of lane can be taken into account in a very straightforward manner during the tracking mode. To do so, the lane model must be replaced by a road model. The boundaries of the previous catchment basin are used to draw not only the model of the current lane but also the adjacent ones. Therefore, we generate as many possible markers as there are lanes. If the car performs a change of lane, the right marker however is selected and injected in the watershed transformation. This marker corresponds to the one appearing in front of the scene (Figure 5). Moreover, the number of the current lane and the drawing of the road model are modified accordingly.

3. Obstacle detection

The second part of the treatment is the obstacle detection. This process is performed in parallel on the regions of interest (ROI) emphasized by the road segmentation. Starting from the position of the lane boundaries, it is easy to compute the coordinates of a window embedding the part of the image corresponding to a given range of distance where the obstacle detection algorithm can be applied.

Principle of the obstacle detection

Three main characteristics of the vehicles are used for their extraction:

- There always exists a darker region in front of the vehicle corresponding to its shadow, the wheels and the bumper. This region can be used as a marker in further segmentation algorithms. Another interesting point is that this region always touches the road.
- The geometry of the vehicles is rather simple. As most of the manufactured objects, vehicles are made of horizontal and vertical contours and their size is a rather constant parameter (between 1m and 1.5m).
- The vehicles are symmetric objects.

Obstacle detection in practice

In practice, among these three main criteria, only the two first ones have been used. Symmetry, although it is a very efficient criterion, has been canceled because of its too long computation time. The darker region is detected by means of a morphological transform called h-minima. The available markers are then filtered and only those which touch the road and whose size correspond to the dimension of a vehicle are kept (Figure 6). These markers can be used in watershed algorithms applied on directional gradient images or, more simply, used as such.

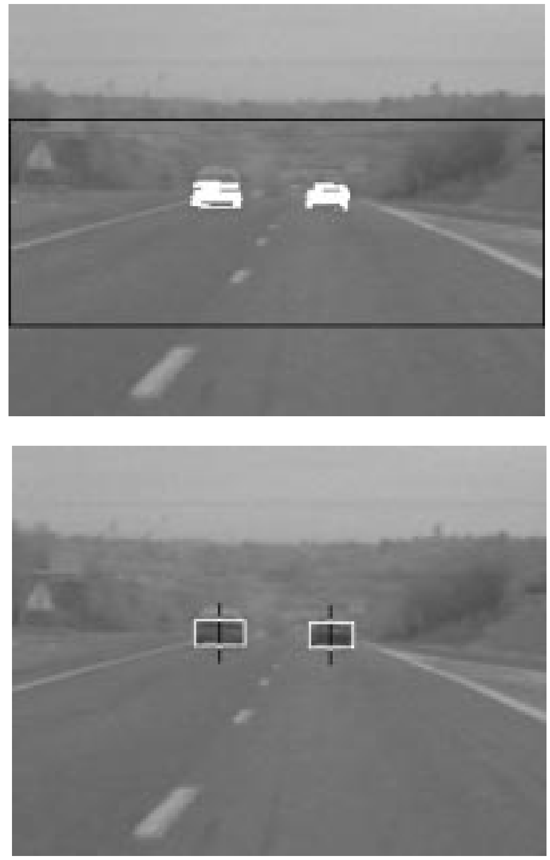

Figure 6: Detection of the dark zone in front of vehicles (up) and corresponding bounding boxes (down)

More refined obstacle segmentation algorithms can also be designed. They are based on hierarchical segmentations [2]. Their complexity comes from the fact that they need two successive watershed transformations. However, thanks to the selection of ROI in the image and to the use of fast watershed algorithms, they are not too time-consuming.

4. Fast watershed algorithm

On non sequential computer hardware, the slowest part of the segmentation is the watershed transformation. This watershed is performed by means of geodesic skeletons of influence (SKIZ) [1]. The simplest way to achieve it consists in processing the successive gray levels of the image E. Let us denote $Z_i(f)$, the section of a function f at level i:

$$Z_i(f) = \{x \in E : f(x) \leq i\}$$

Given two sets X and Y, with $X \subset Y$, the geodesic SKIZ of X inside Y is denoted by SKIZ(X;Y). This set is made of the zones of influence in Y of the various connected components of X. A zone of influence of a connected component contains all the points of Y at a lower geodesic distance from that connected component than from any other component. The watershed transformation WTSM(f) of the function f controlled by a marker set M, can then be obtained by iterating the following formula for all the sections $Z_i(f)$:

$$W_{i+1}(f) = \mathrm{SKIZ}(W_i(f); Z_{i+1}(f) \cup M)$$

with:

$$W_{-1}(f) = M$$

At the end of the procedure, when the highest gray level n is processed, we have:

$$WTS_M(f) = W_n(f)$$

When the watershed is not marker-controlled, the algorithm remains the same with M = m(f), minima of f.

Despite the fact that the hardware processor designed for this project is equipped with eight PIMM1 circuits allowing to perform in a simple pass up to 64 elementary binary morphological transformations, this processor remains too slow for achieving a real-time watershed. A possible solution for increasing the computation speed leads in the reduction of the gray levels. This reduction is made by means of an anamorphosis. An anamorphosis ϕ is a monotonous increasing mapping of f:

$$f \to \phi(f)$$
$$\forall x, y: \ f(x) < f(y) \Leftrightarrow \phi(f(x)) < \phi(f(y))$$

However, if we reduce the number of gray levels in an image, chances are, in the discrete case, that the watershed of $\phi(f)$is dramatically different from the watershed of f. In fact, if the watershed is marker-controlled, the difference between $WTS_M(f)$ and $WTS_M(\phi(f))$ is not very important because, in both cases, the watershed lines take place on the highest zones separating the markers. Now, the highest zones of f correspond also to the highest zones of $\phi(f)$. But, if the watershed of f is a simple watershed, the minima m(f) will be very different from the minima $m(\phi(f))$. The solution for getting similar watershed transforms consists in performing a marker-controlled watershed of $\phi(f)$ with the minima of f:

$$W_{i+1}(\phi(f)) = \mathrm{SKIZ}(W_i(\phi(f)); Y_{i+1})$$

with:

$$Y_{i+1} = Z_{i+1}(\phi(f)) \cup M$$

where:

$$M = m(f)$$

Among the various available anamorphoses, the following one is very efficient on gradient functions:

$$\phi(f) = \log_2(f+1)$$

This transformation leaves the low values practically unchanged and decreases significantly the high values. An image defined with 256 gray levels is then reduced to height gray levels. Thus the computation speed is multiplied by 32, with a slight degradation of the watershed transform as illustrated in Figure 7.

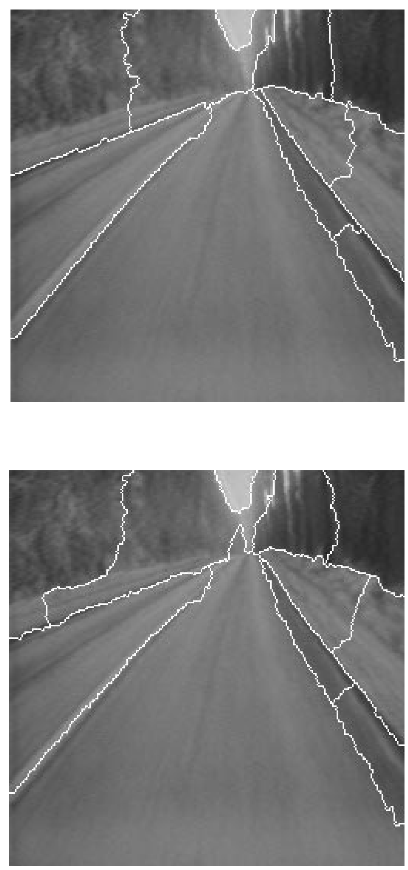

Figure 7: Comparizon of watershed transformations: true watershed (up) and watershed obtained with an anamorphosed image (down)

5. Conclusion

The fast watershed algorithm based on anamorphosis leads to robust and efficient segmentation procedures. This transformation applied on a 256x256x8 bits picture is achieved in less than 80 ms. So, we are able to process each scene in a period of time which never exceeds 200 ms. Experience has proven that this computation rate (5 images/s) is enough to provide the supervision process with the whole information regarding obstacles.

6. References

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