ROAD RECOGNITION IN COMPLEX TRAFFIC SITUATIONS

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Abstract. This paper describes the algorithms for road edge detection in complex traffic situations by an on-board video camera. The information that comes from the motion of a dynamic scene is used to build a new family of filters called Dynamic Time Filters (DTF). These filters apply morphological opening and closing transformations to the image sequence provided by the camera. This sequence is considered as a 3D image. The DTF-filtered image is segmented by means of the watershed transformation. Two different modes have been implemented for the segmentation. The acquisition mode allows an initial extraction of the current traffic lane. It also produces initial markers which will be used by the second segmentation mode, where an interpolated road/lane model is used to follow and segment the lanes.

Some results of the segmentation process are given in complex situations to illustrate the efficiency and robustness of this approach. Information is also given on the real-time performance of the algorithms implemented on a car demonstrator.

Key Words. Road segmentation, morphological filter, dynamic time filter, watershed transformation, road model, inboard image processor, Prometheus project, mathematical morphology, image analysis

1. INTRODUCTION

The Prometheus project is a European Eureka program which aims at improving road traffic and its safety by means of high level technologies and especially image analysis. The Center of Mathematical Morphology is involved in this project with other French research laboratories and car manufacturers (Renault, PSA) for designing a car demonstrator, named Prolab2. Our contribution to this demonstrator is the development of a real-time on-board image processor for analyzing traffic scenes provided by front or rear view video cameras. This sensor works in parallel with other devices (telemeter, stereovision system, motion detector) and sends information to a supervisor delivering messages, recommendations and warnings to the driver (Fraichard *et al.*, 1992). The two main tasks of our sensor are first, segmentation of the road and of the traffic lanes and, second, obstacle detection. The latter task will be presented elsewhere (Yu, Beucher, 1994).

This paper is devoted to the presentation of the algorithms used for road and traffic lanes segmentation. Although it exceeds the scope of this paper, some details will also be given on the implementation of these algorithms in the real-time image processor.

The purpose of the segmentation is twofold: on the one hand, it provides useful information on the car position, its heading, the number of traffic lanes, the nature of the ground marking and, on the other hand, it allows to compute the coordinates of regions of interest in the scene where other sensors or processes can act, in particular obstacle detection. Applying the obstacle detection algorithms in selected regions has a great advantage: it reduces the size of the image to be investigated. thus it reduces the computation time and it increases dramatically the robustness of obstacle detection by rejecting artifacts and false alarms.

The road edge recognition in a traffic scene taken by on-board cameras is a very active problem dealt with by many researchers in the world (Dickmanns *et al.*, 1988; Masaki, 1991). But the existing algorithms to this end impose too many hypotheses to simplify the problem. It is often assumed that road edges are marked by ground markers, that there is no vehicle occluding the road edges, that there is no shadow on the road and so on. These hypotheses cannot be verified in real traffic situations, and more general algorithms must be designed in these cases.

2. LANE SEGMENTATION ALGORITHMS

Although these algorithms have been mainly used on roads with central and lateral ground marking (continuous or not) and in daylight conditions, they also work efficiently when there is no ground marking. In this case, however, the entire road will be extracted.

Two different processes must be used for lane segmentation. The first one is an initialization step: knowing nothing on the scene to be analyzed and on the position of the vehicle on the current traffic lane, we must be able to perform a first extraction of this current traffic lane. This mode of segmentation is called the acquisition mode. As soon as this first segmentation is available, another process can be activated which is supposed to be faster and more robust. This process uses the last segmentation to match a computed model of the lane with the next image. This model leads to a new segmentation used to update the road model. This mode is called the tracking mode.

These two processes use the same morphological segmentation tool: the watershed transformation. It would be too long to recall here the definition of the watershed as well as the principle of its use. The reader is invited to refer Beucher *et al.* (1992) for further details. It must be reminded however that the objects or regions to be segmented in the image by this method must be marked first. Then, a segmentation criterion must be defined. Most of the time, it is a contrast criterion, but that is not compulsory. This criterion is materialized under the form of a function to which the watershed transformation is applied. Markers of regions are then combined with the criterion function. Its topology is modified and its watershed lines are detected. Thus, they correspond to the boundaries of the regions to be segmented (see Fig.1).

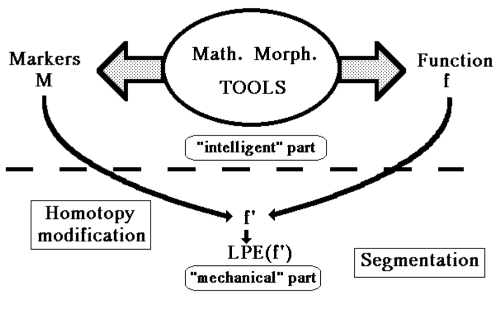

Fig. 1. Principle of the watershed segmentation

We will see that the two algorithms used in traffic lane segmentation share the same criterion function. Only the markers used for detecting the lanes differ.

2.1. Building the criterion function with a dynamic time filter

The first task consists therefore in defining a criterion function to segment the road and the traffic lanes. If the contrast between the roadway and the edges is an important criterion, unfortunately it is not sufficient because the ground marking is not always continuous. Then there exists no physical separation between the traffic lanes. It is therefore necessary to construct it. Various geometrical techniques can be used. However, the use of a dynamic time filter (DTF) applied to successive images of the sequence provides an efficient solution to this problem (Yu, 1993). At any moment i, a sequence of images $\{f_i\}$ is available as a source of information. This sequence can be considered as a 3D image. Any pixel in this 3D image has two spatial coordinates and one time coordinate. Simple morphological transformations as dilation and erosion can be defined on this 3D image. By choosing a rectilinear structuring element oriented along the time axis, one defines purely time transformations. Thus the size n time dilation $TD_n(fi)$ and erosion $TE_n(fi)$ are defined by:

$$TD_n(f_i) = \sup_{i-n\leq j\leq i} \left(f_j\right) \quad (1)$$

$$TE_n(f_i) = \inf_{i-n\leq j\leq i} \left(f_j\right) \quad (2)$$

By combining these elementary transformations, one defines time openings and closings, then more complex morphological filters (time alternate sequential filters). The closing is given by:

$$TC_n(f_i) = TE_n[TD_n(f_i)] \quad (3)$$

$$TC_n(f_i) = \inf_{i-n\leq j\leq i}\left(\sup_{j-n\leq k\leq j} (f_k)\right) \quad (4)$$

An alternate sequential filter is a combination of openings and closings of increasing sizes:

$$TO_n \circ TC_n \circ ... \circ TO_1 \circ TC_1 \quad (5)$$

These DTF give very good results, especially when the initial operator is a closing. Fig.2 illustrates the effect of such a filter on the image. The size of the structuring elements (that is the number of successive images taken in the sequence) depends upon the speed of the vehicle. This DTF has several favorable effects that make the segmentation procedure much easier. In particular:

1/ The DTF eliminates noise without blurring road edges. Moreover, it adapts itself automatically to perspective distortion.

2/ The different kinds of shadows, the dust lying on the pavement are suppressed.
3/ It eliminates the obstacles occluding road edges. This feature could be considered as a major drawback. In fact it is not the case because obstacle detection is not the task devoted to the road segmentation module.
4/ The discontinuous ground markers are connected to form a continuous line separating the traffic lanes.

(a)

(b)

Fig. 2. DTF by closing (b) of the original sequence (a) connection of the ground marking

The construction of a real separator between the lanes is achieved by this means. Thus, a criterion function is available for the segmentation algorithm based on the watershed transformation.

The DTF transforms a complex road, which is originally not uniform because of the presence of shadows, vehicles and other objects, into a uniform simple road divided by continuous ground markers.

2.2. <u>The acquisition mode</u>

In this first mode, the extraction of the region corresponding to the current traffic lane is obtained by applying the watershed transformation to the gradient of the DTF-filtered image. In fact, the gradient used is not a simple gradient, but a combination of two more sophisticated morphological operations:
- A top-hat transformation of the DTF-filtered image is performed. The top-hat transformation of a function f is defined by:

$$TH_k(f) = f - O_k(f) \quad (6)$$

where O_k is the spatial size k opening of f.
- A morphological regularized gradient g* is calculated (Beucher, 1990). The regularized gradient is built from a "thick" morphological gradient g_k of f:

$$g_k(f) = D_k(f) - E_k(f) \quad (7)$$

D_k and E_k being respectively the spatial size k dilation and erosion.
Then a top-hat transformation is applied to g_k, followed by an erosion of size k-1:

$$g^*(f) = E_{k-1}[TH_k(g_k(f))] \quad (8)$$

This transformation based on the simple morphological gradient produces a smoother image, with a lot of non significant minima which have been removed and the corresponding homogeneous regions are not over-segmented by the watershed.
The sup of the two transforms provides the image to which the watershed transformation is applied. Although each lane is not necessarily uniform, no over-segmentation occurs thanks to the smoothing effect of the DTF and of the regularized gradient (see Fig.3).

Fig. 3. Watershed of the DTF-filtered image

Some binary morphological transformations (hole filling and opening) are then used to remove irregularities. The region in front of the camera is selected by a binary morphological reconstruction. If it satisfies the geometric characteristics of a traffic lane (especially with a width conform to the standard of traffic networks), it is considered as a lane and the acquisition mode can be followed by the tracking mode.

2.3. The tracking mode

Once the road or lane edges are recognized, the perception system switches to the tracking mode.

In this mode, according to the segmentation paradigm given in Fig.1, the watershed transformation is applied with markers, which are built from the previously detected lane marker. This lane marker may be the result of the previous segmentation step in the tracking mode or in the acquisition mode. The previous marker is eroded whereas its eroded complementary set is used as outer marker. Although no DTF-filtered image is required in this mode because the watershed transformation with previously defined markers can extract directly the lane edges from the current image in spite of the occurrence of other objects inside or across the road, the DTF-filtered image is used to increase the robustness of the segmentation. However, in order to be sure that the detected edges will pass through the ground marking of the current image, the latter image is mixed with the DTF-filtered image. The resulting image f'_i is obtained by:

$$f_i' = \sup[DTF(f_i), f_i + 1] \qquad (9)$$

Fig. 4. Points of the watershed line belonging to the ground marking

The catchment basin of the watershed corresponding to the lane is extracted and its boundary points belonging to the ground marking of the current image are selected. These points are used to calculate a polynomial approximation of the lane (see Fig.4). This lane approximation can be drawn and its parameters (coefficients of the polynomial function) lead to some information on the road geometry, the relative vehicle location and heading, distance measurements, perspective data (vanishing point), etc. . Finally, the lane approximation is used as marker for the next segmentation step (see Fig.5).

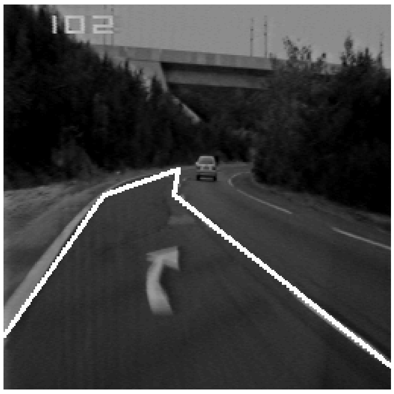

Fig. 5. Calculed lane model (this model is made of two linear portions)

3. RESULTS & REAL-TIME IMPLEMENTATION

3.1. Some examples, performances

Numerous tests have been made on a large database composed of 4000 images taken from different sites under various conditions. Fig.6 to Fig.9 illustrate these two modes of detection through some representative results obtained from front or rear view scenes.

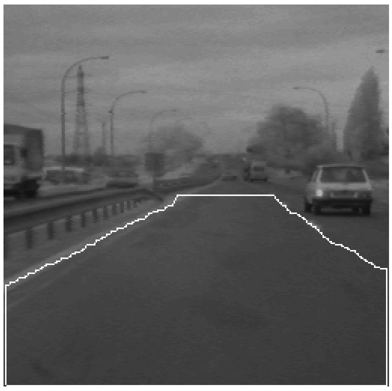

Fig. 6. Segmentation of the lane in acquisition mode

The acquisition mode assumes, to operate correctly, that the vehicle remains on its traffic lane. Moreover, the presence of too close obstacles must be avoided. However, as it is an initialization process, one can wait that these optimal conditions are fulfilled to switch to the tracking mode. In both modes, the quality of the result can easily be acknowledged since it suffices in most cases to verify that the geometry (topology, dimensions) of the resulting region is compatible with the characteristics of a standard lane. The tracking mode is rather robust. Lane changes especially are properly managed. Notice also that it is not necessary to define markers for all the traffic lanes of the road. Indeed, if the number of lanes and the position of the lane where the vehicle is driving are known, the road / lane model can very easily calculate and trace the boundaries of the adjacent lanes (see Fig.10). It is even possible to verify the existence of adjacent lanes by checking that there actually exists an edge or a ground marking under the border traced by the road model.

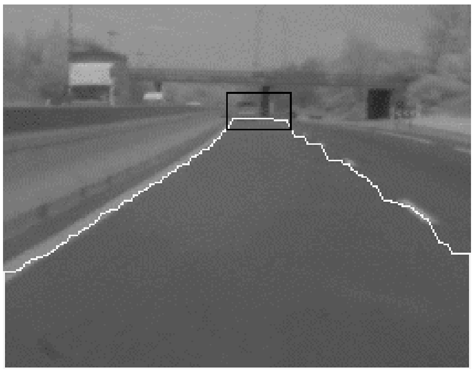

Fig. 7. Another example of the acquisition mode with determination of the obstacle detector 's ROI

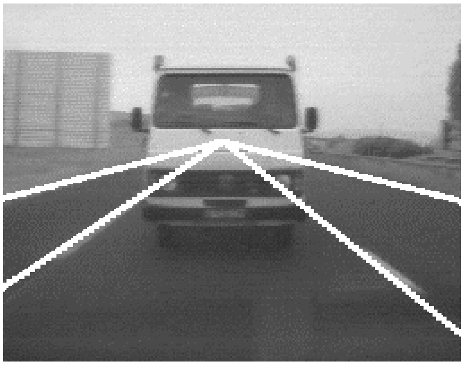

Fig. 8. Segmentation in tracking mode (rear view)

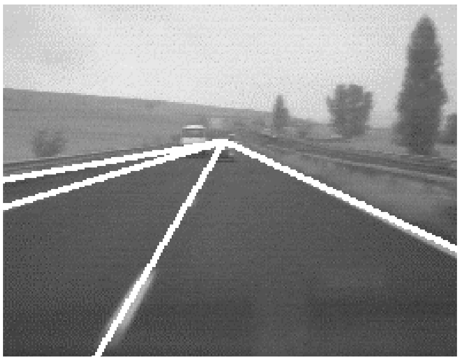

Fig. 9. Segmentation in tracking mode during a lane change

3.2. <u>Speed of computation, real-time implementation</u>

The real-time morphological processor which is installed on-board the Prolab2 demonstrator is supposed to achieve a road / lane segmentation every quarter of a second on a 256x256 image. To reach this goal, a special machine architecture has been designed. This architecture is based on a mathematical morphology integrated circuit named PIMM1 (Peyrard *et al.*, 1991; Bilodeau *et al.*, 1992). The on-board image processor includes eight PIMM1 chips. However this computing power is not sufficient to complete the segmentation in the requested time. This is the reason why the algorithms used have been simplified and in particular the DTF filters. If the quality of images is sufficient, time dilations can even be used instead of closings. similarly, the computation speed of the watershed transform has been deeply improved by using a technique based on anamorphoses. It is also possible to limit the segmentation of the traffic lanes on the forestage of the image, especially in the case of rear views.

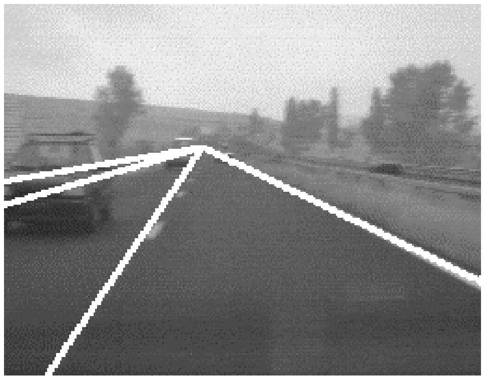

Fig. 11. The road model allows a perfect segmentation of the lanes although they are hidden by obstacles

4. CONCLUSIONS

Road / lane segmentation is a background process aiming at defining regions of interest in the traffic scene. These regions of interest allow then to focus the detection of obstacles and to locate accurately our vehicle. These two tasks can be performed efficiently thanks to the use of a road model fitted to every image of the real sequence. But this model has also another great advantage: it is a crucial part of the segmentation process because the computed road/lane interpolation at step n is used to generate the lane marker which will be introduced in the watershed transformation for the segmentation at step n+1.

The robustness of this approach has been tested and proved in various complex situations. The detection of adjacent lanes and the management of lane changes are particularly efficient.

Numerous measurements derived from the segmentation and the road model are available: location and heading of the vehicle, distance measurements, nature of the ground marking (continuous or discontinuous), curvature of the road and so on. Combined with the obstacle detection module, a complete system of perception is operating, providing information on potential obstacles in the traffic scene.

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