ROAD SEGMENTATION BY WATERSHEDS ALGORITHMS

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ABSTRACT: *A road segmentation technique is proposed based on a mathematical morphology tool called watershed transform. Starting from a coarse marker of the road to be segmented, we modify the gradient image of the scene and compute the watershed transform of this image. The result provides a fair segmentation of the road. The marker itself is produced by using the watershed transform, and a simplified representation of the initial image called graph-partition. The watershed transform allows a hierarchical description of the graph-partition image then used for marker extraction. The whole algorithm robust, little sensitive to noise and need no parameter setting. Other technique for selecting markers are also described. Many examples in various traffic situation are given.*

INTRODUCTION

The Centre of Mathematical Morphology (C.M.M.) of the Paris School of Mines is one of the French image analysis laboratories involved in the the European project PROMETHEUS (Vision Group). This paper presents some of the CMM's works and future perspectives. At the beginning of the project, two different ways of research were studied. The first one used classical image segmentation algorithms. The second one used the segmentation tools of mathematical morphology for extracting the road and possible obstacles. The first one have been described in [4].

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1. PROJECTS GOALS

The purpose of the study was to elaborate image processing algorithms for a driving assistance, and more precisely to extract vehicle position on the road, and possible obstacles. We mean by obstacle everything that could hold up the vehicle on the road, whether this obstacle is a cooperative one (another vehicle on the road) or not (object on the road, pedestrians crossing the road, etc.).

In the first step, these two tasks require both an automatic road detection. This detection must work for any kind of road (highway, country road, and so on). The different infrastructures of such roads, and in particular the lane markers, impose general and robust detection algorithms.

Our main work deals with the development of road detection algorithms. These algorithms have been tested on a small image database representing about thirty driving situations. We also work on obstacles detection by pointing out images regions with possible obstacles.

2. THE IMAGE DATABASE

The images used in this study have been acquired by PSA and RENAULT. They are representative of a large number of road scenes different driving situations. Different kinds of B&W camera have been tried with different image quality in order to test the robustness of the algorithms.

The images are digitized in a 512x512x8 square grid format and stored on IBM-PC under MS-DOS (figure 1). This straightforward file format allows easy file transfers. The host computer is linked to a MORPHOPERICOLOR image processor designed by the CMM. This proces s or comprises a complete mathematical morphology toolbox. The images processed by the Morphopericolor are on a 256x256x6 format in hexagonal grid.

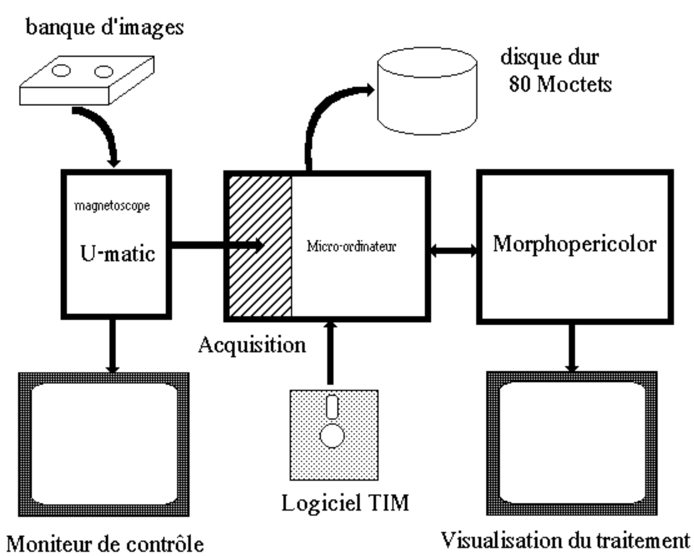


Figure 1: Block diagram of the image processing system

3. IMAGE PROCESSING

Two approaches have been used for the road detection. The first is based on the segmentation of the image by edge and region detection (X. YU, 1989, [4]). The results are good enough when the contrast of the images is sufficient. These approach needs, however, the setting of many parameters, which compromise the robustness of the process.

The second approach uses exclusively morphological segmentation tools for based on a transformation called watersheds [3]. Image segmentation by watersheds is a technique of segmentation based on the marking of the objects to be extracted. This marking is the fundamental step of the process. We will discuss more about these tools in the next sections.

3.1 Image Segmentation. An overview

A grey-tone image can be considered as a positive function f. Let us define on this function two morphological transformations: the morphological gradient and the watershed transformation.

3.1.1 Morphological Gradient

The morphological gradient g of a function f is defined by:

$$g(f) = [(f \oplus H) - (f \ominus H)]$$

where $(f \oplus H)(x) = \operatorname{Sup}_{y \in H_x} (f(y))$ is the dilation of f at the point x

and $(f \ominus H)(x) = \operatorname{Inf}_{y \in H_x} (f(y))$ is the erosion of f

(H is the elementary hexagon on an hexagonal grid).

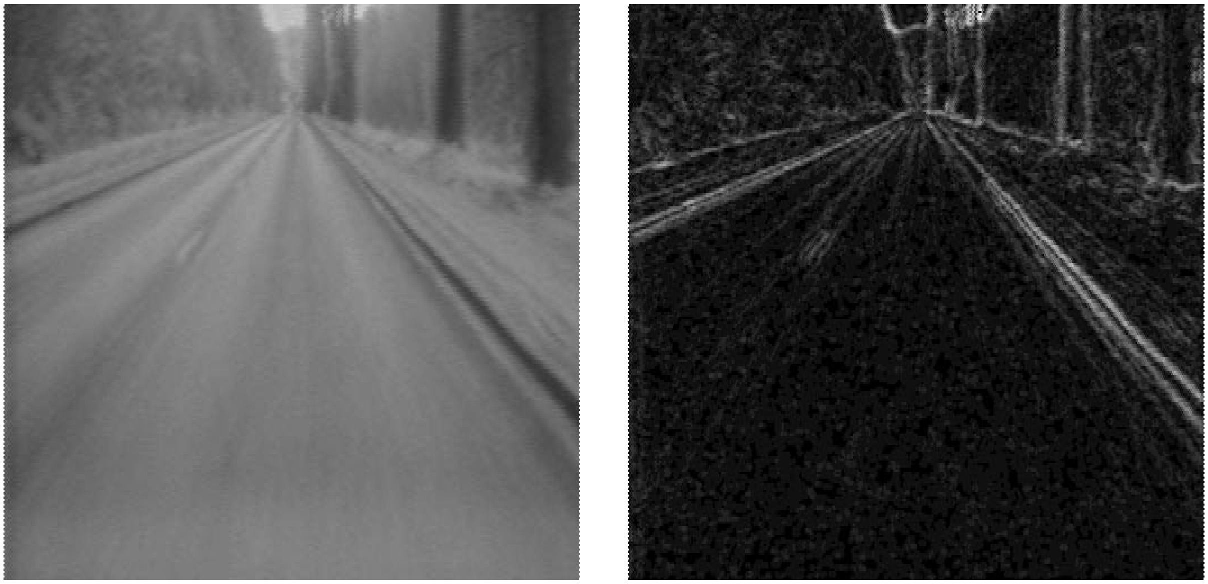


Figure 2: *a) Original image and b) its morphological gradient*

3.1.2 Watershed transformation

The watershed transformation is more complex. Let us give an intuitive definition of this operation by considering the graph of f as a topographic surface. This surface presents minima, which are connected regions where it is not possible to reach a point at a lower altitude by an always descending path (figure 3).

Suppose that minima are pierced and that the topographic surface is immersed in water. The water will pour through the holes, through the deepest ones at first, and will progressively flood the surface. While flooding, we build dams at any point where waters coming from two different minima may merge. At the end of the flooding, divide lines appear, called watersheds of the function f. The different connected components separated by the watershed lines are called catchment basins, each on being associated to a single minimum (figure 4).

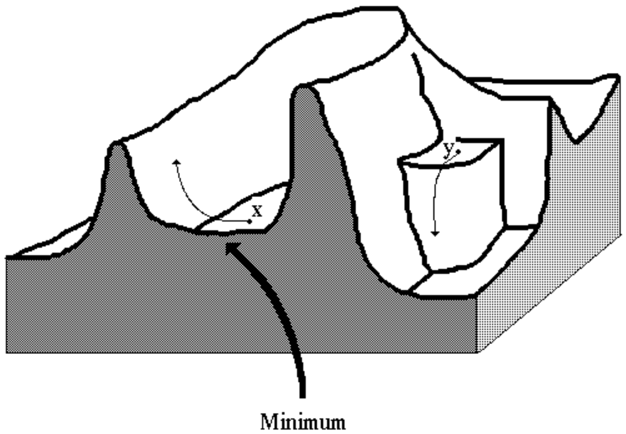


Figure 3: *Minima of a function*

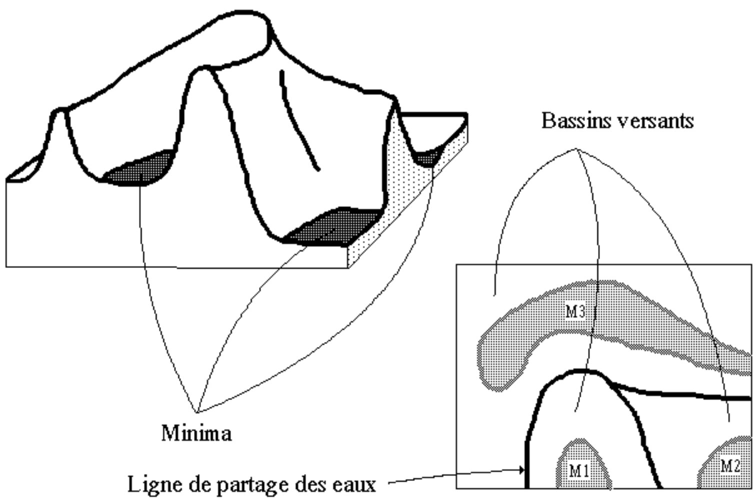


Figure 4: *Watershed and catchment basins*

Segmentation by watersheds is based on the following assumption: any object in a image is characterized by a homogeneous texture and hence a weak gradient. The objects in an image correspond therefore to the minima of the morphological gradients, and their contours to the watersheds of the gradient.

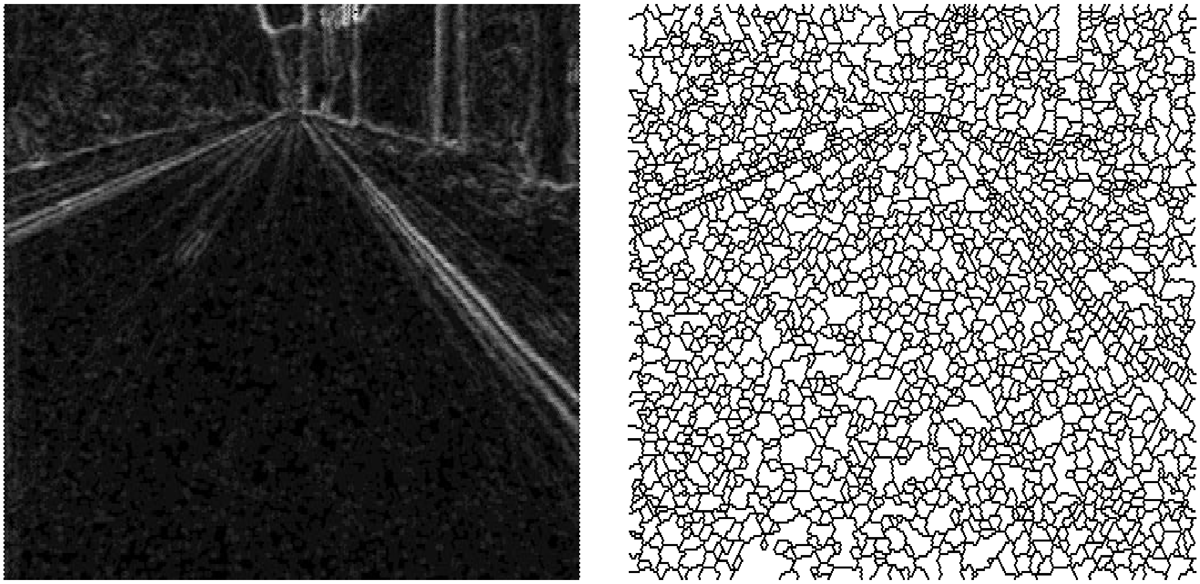


Figure 5: *Watershed of the gradient image. Noise, inhomogeneities produce many catchment basins*

3.1.3 Markers Oriented Segmentation

If the principle of the segmentation by a simple watershed of the gradient is appealing the results aren't. Noise and inhomogeneities produce a lot of minima which lead over-segmentation of the image (figure 5).

The procedure can be enhanced if we define new markers for the objects to be extracted. These markers are obtained by various means, which will be discussed later. These markers are then imposed as the new minima of the gradient. Doing so, we modify the gradient function. As a result, the only minima of this modified gradient are the imposed markers. This modified function nevertheless, is close enough to the original gradient function to preserve the edges. This modification is performed with geodesic image reconstruction.

Let M be the set of markers:

$$M = \bigcup_i M_i \qquad M_i \text{, connected component } (M_i \cap M_j = \emptyset,\ \forall i \neq j).$$

Consider the function h defined by:

$$h = a (1 - k_M)$$

where a is the upper limit of the gradient g, and k_M the indicator function of M. We define the reconstructed function g' as the result of the iterative following operation:

$$\begin{array}{l} \text{REPEAT} \\ \quad g_o = h \\ \quad g_n = \text{Sup}\ (g_{n-1} \ominus H,\ g) \\ \text{UNTIL}\ g_{n-1} < g_n \\ \ g' = g_n \end{array}$$

We notice (figure 6) that the minima of g' are the connected components M_i.

The contours of the marked objects are then the watershed lines of g'.

In this approach, the image segmentation is composed of two independent steps. The first and most critical step consists in finding markers for the objects to be extracted. The second one consists simply in modifying the gradient function and computing the watersheds.

3.2 Road Segmentation Algorithm.

Two different algorithms have been used for road segmentation:

- The first one uses a regularized morphological gradient which reduce over-segmentation.

- The second one starts from a simplification of the original image. This simplified image along with its gradient are used to extract homogeneous regions.

These two marking techniques are nonparametric. They are simply based on the different of contrast between the road and its border.

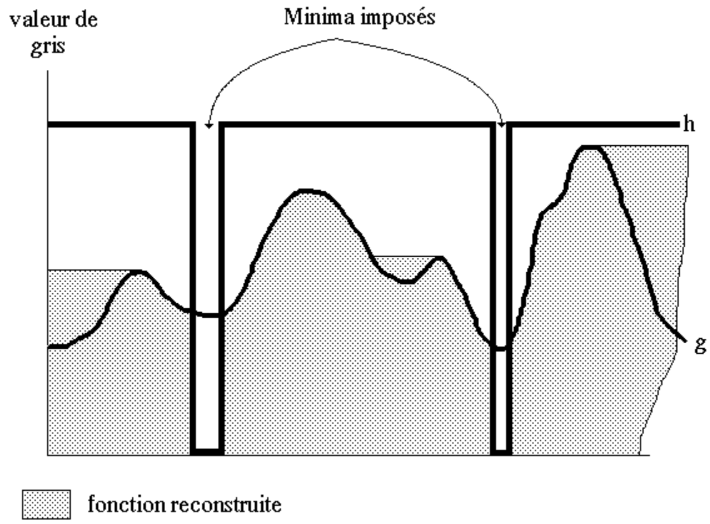


Figure 6: Reconstruction of a function by erosion. The marking function h becomes closer to the initial function g by imposing its minima.

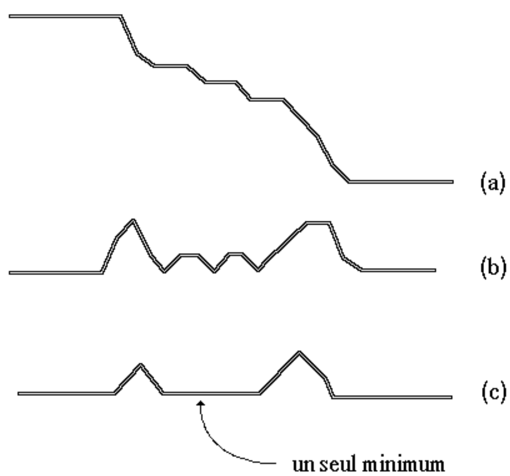


Figure 7:Regularized gradient. a) initial function, mono dimensional case b) morphological gradient c) regularized gradient

3.2.5 Segmentation with regularized gradient.

The regularized gradient of size i of the function f is the transform defined by:

$$u_i(f) = \left[(g_i(f) - ((g_i(f) \ominus H_{i+1}) \oplus H_{i+1})\right] \ominus H_{i-1}$$

with :

$$g_i(f) = (f \oplus H_i) - (f \ominus H_i)$$

This operation depends of size parameter. We can although define a non-parametric transform by computing the supremum of all u_i:

$$g^* = \operatorname{Sup}_i (u_i)$$

Other similar transforms could be used. The main advantage of the regularized gradient is its ability to take into account the variations of the initial function (figure 7).

The watershed of g*, as shown in figure 8, is less over-segmented than the watershed of g.

This first segmentation can now be used for extracting a coarse marker of the road. This marker is obtained by selecting the catchment basin of W(g*) located at the front of the vehicle(figure 9).

This marker is smoothed and an outer marker is built in order to mark the region of the image which do not belong to the road (figure 10).

These two markers M1 and M2 are used to modify the gradient g (figure 11). The divide lines of the modified gradient are the contours of the road.

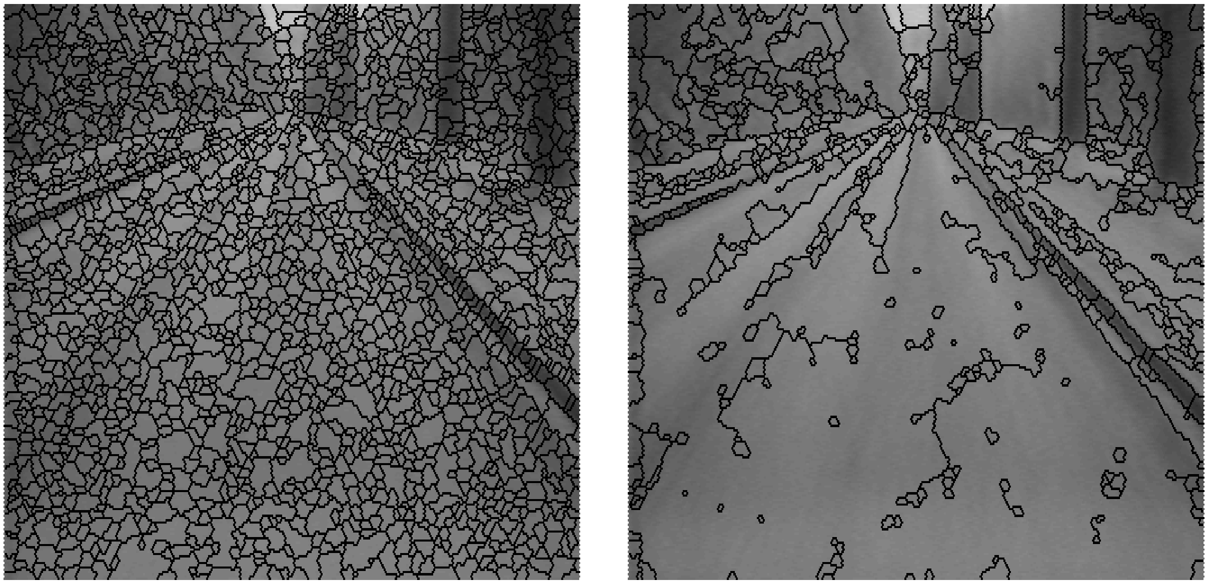


Figure 8: *Watershed of the regularized gradient in b) compared to the watershed of the simple gradient in a)*

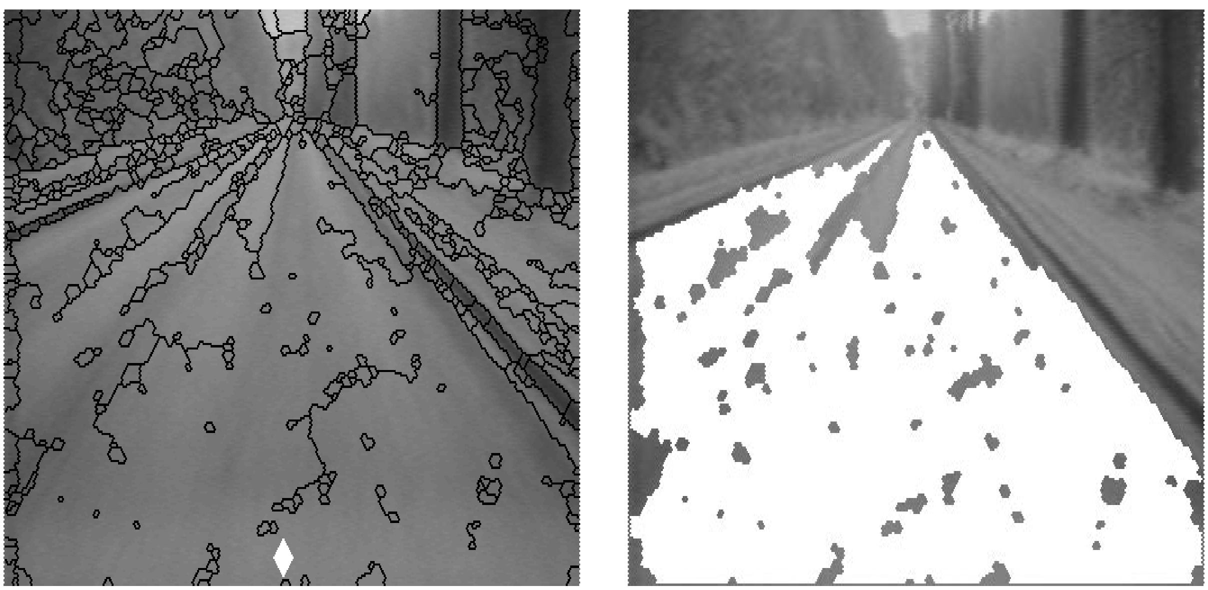


Figure 9: *Extraction of a primitive marker of the road. a) Watershed of g* and pointer in front of the car b) extracted marker*

3.2.2 Segmentation Using a Simplified Image

Road markers are obtained by image simplification. A simplified image f' is built starting from the image f and its gradient g(f).

Let's consider the minima M of g and let's define a function h as follow:

$$h = f \cdot k_M$$

where k_M is the indicator function of M.

Let's compute the geodesic reconstruction of h by dilation inside the catchment basins. This operation produces an image where each basin of g is valued. This valuation leads to a simplified image f' made of tiles of constant grey values (figure 14). This image is called the mosaic-image.

The gradient of this mosaic-image may be defined. This gradient will be null everywhere except on the divide lines of g where it is equal to the absolute difference between of the grey-tone values of the catchment basins CB_i and CB_j separated by C_{ij} (figure 15).

$$\mathrm{Grad}\ (C_{ij}) = |f_i - f_j|$$

This gradient-mosaic image is then used to define a new function v. We have:

$$X_i(v) = \{x : v(x) \leq i\}$$
$$X_i(v) = \bigcup_j CB_j$$

where the CB_j are the catchment basins adjacent to any arc with a watershed of the gradient-mosaic less or equal to i.

The watersheds of this function point out the regions of the image surrounded by higher contrast edges (figure 15). The figure 16 compare the results of these two algorithms with the one with the regularized gradient. We can still extract a marker for the road, and use it to modify the gradient image.

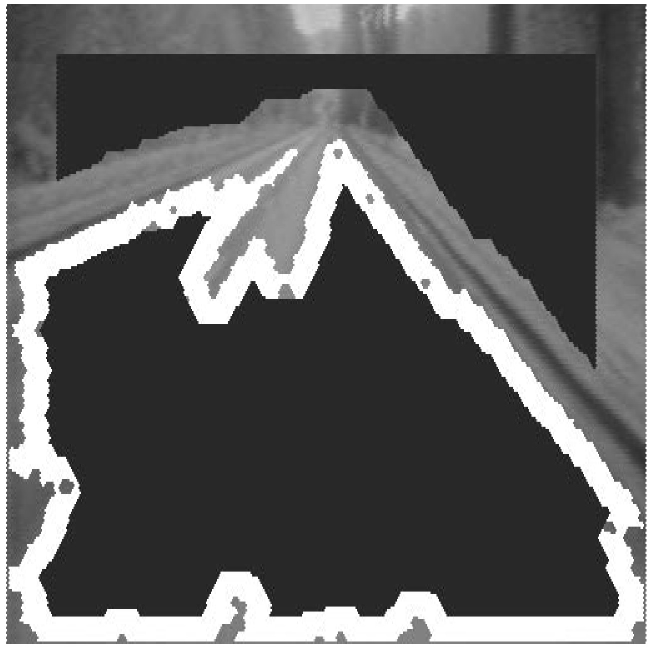


Figure 10: *Chosen markers*

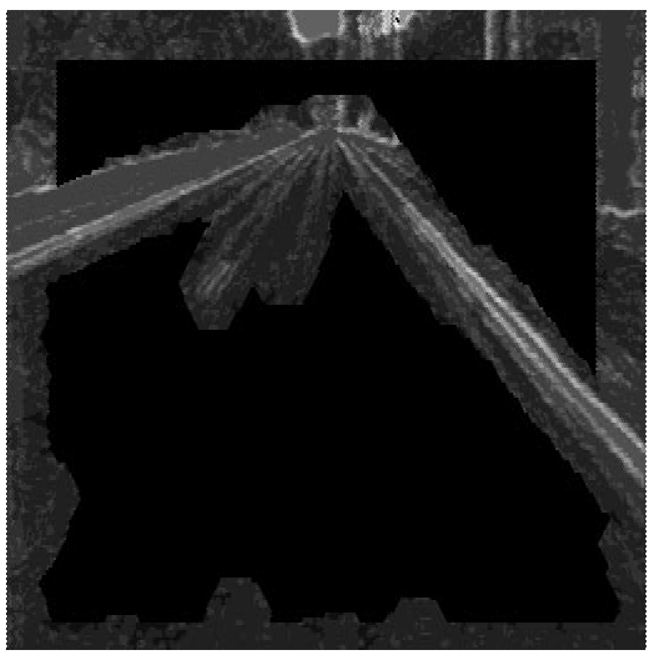


Figure 11: *Modification of the morphological gradient. The previous markers are injected in the gradient g which is modified. The final gradient g' presents only two minima.*

Figure 12: *Road borders. The borders correspond to the watershed of g'*

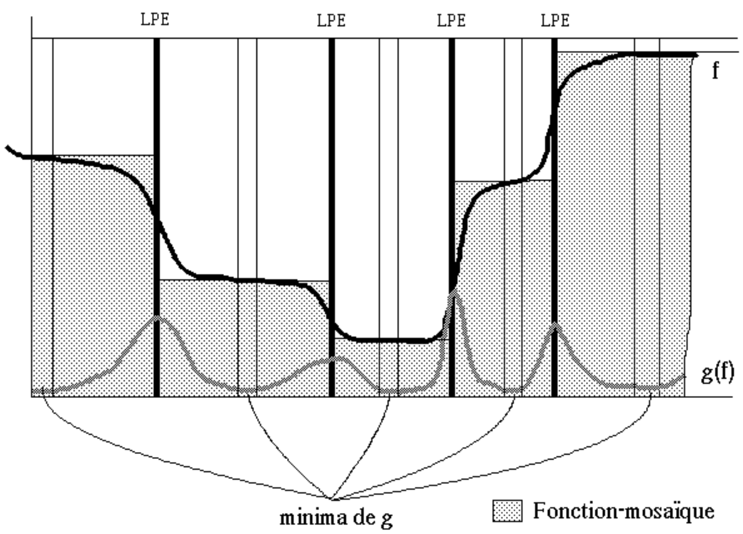


Figure 13: *Principle of the definition of the mosaic-image. The catchments basins of the gradient take the grey values of f corresponding to the minima of g(f).*

Figure 14: *Example of a mosaic-image a) original b) mosaic-image*

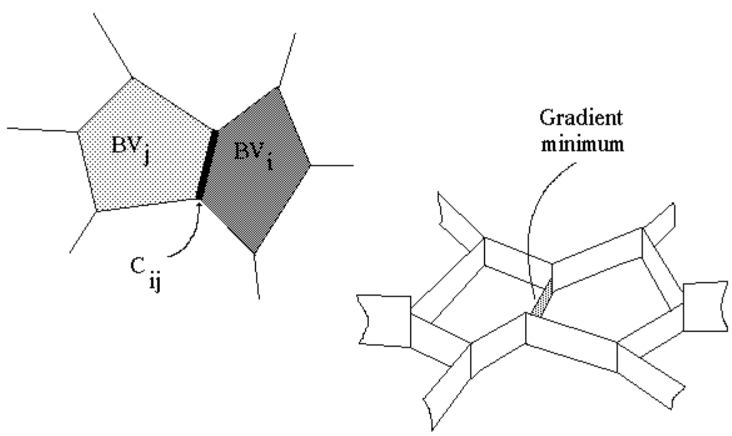


Figure 15: *Gradient of the mosaic-image. a) gradient of C b) gradient graph*

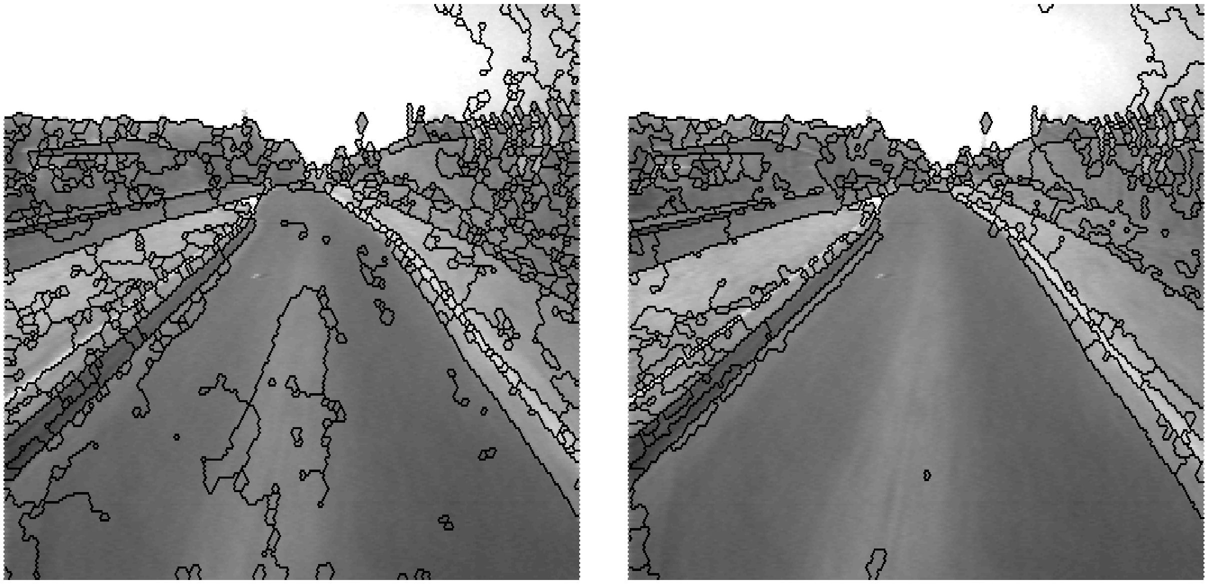


Figure 16: *Comparison markers obtained with the two algorithms. a) watershed of the regularized gradient b) watershed of the mosaic-image.*

3.3 Complementary Processing

Various procedures are available to emphasize the road detection. We can, for instance , segment the road lane by lane provided that some markers exist, even if they are not continuous. We can easily detect this lane markers by a top-hat transform.

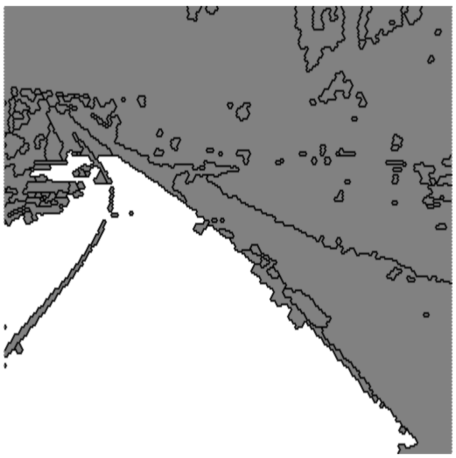
$$TH(f) = f - (f)_{iH}$$

where $(f)_{iH} = (f \ominus iH) \oplus iH$.

This operator extracts elongated objects whiter than their background. By keeping only long, thin and white object inside the road, we can cut the primitive mask of the road into its different traffic lanes (figure 17).

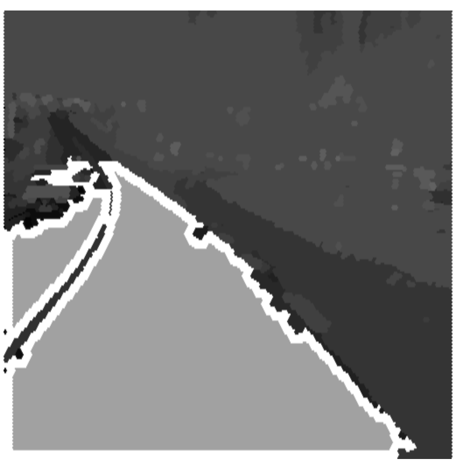
(a)

(b)



(c)

(d)



(e)

(f)

Figure 17: *Lane by lane road segmentation. a) original image b) mosaic-image c) watershed of the gradient of the mosaic-image and primitive markers d) ground layout detectione) lanes markers enhancement f) final result*

4 POTENTIAL OBSTACLES DETECTION

The second task of this study consists in detecting obstacles on the road. As already mentioned [1], this detection is useless without a good definition of the nature of the obstacles in one hand and the purpose of this detection. In fact, a detection only based on by simple image analysis is almost impossible if we simply refer to the variety of possible obstacles. Cooperative or predictable obstacles could be detect in the 2D image by analyzing their geometry if we know where to detect them. That is why we took a certain amount of time to develop algorithms for extracting masks of the road. However, unpredictable obstacles being by definition of arbitrary geometry, it is thus inconceivable to detect them by 2D image analysis. Moreover, how can we distinguish a dangerous obstacle from a light variation in intensity due, for instance, to a shading? To answer this question, we need more information about the 3D shape of the objects under study. This information could be provided by a telemetric sensors or by stereovision.

For all these reasons, the second phase of the study consists only in detecting potential obstacles without verifying their reality and their degree of risk. We simply find in the image using the road segmentation, regions where obstacles could be. As an example, in figure 18, the road segmentation delimits a zone in front of the car which corresponds to an obstacle-free region. A simple operation (linear opening) is used to detect regions of the road with possible obstacles (figure 19). The region in front of the free zone could then be explored by telemetry or stereovision to verify the nature of the obstacle. A telemetric system can be focused to the delimited zone the measured distance can be compared with the estimated one.

Figure 18: *Road segmentation with obstacles*

Figure 19: *Obstacle-free zone. In black the edges of the road. In white, zone without obstacles in front of the car.*

Figure 20: *Analyzed scenes*

5 RESULTS AND VALIDATION

These segmentation and obstacles detection algorithms have been tested on an image bank containing road and highway scenes on day time under good weather conditions. Some of the scenes are represented on figure 20. Two recording campaigns have been made and though images from the second have a better contrast, the results are similar.

The two marking techniques we described in the last sections are relatively equivalent. The second one give better located markers when the contrast is high enough.

Results with near and far obstacles are given (Figures 21 to 24). A lane by lane detection has not been made. In all the situations, the obstacles were cooperative. Figures 25 and 26 illustrate road segmentation without obstacles on highway (figure 25) and on a secondary road (figure 26). The process gives also good results when a curved road is analyzed (figure 27). Finally, figure 28 shows a segmentation on low contrast image. The edges of the road are irregular but perfectly usable.

Figure 21: *Segmentation with near obstacles. Notice that segmentation is fuzzy when the contrast is low.*

FIgure 22: *Near obstacles.*

Figure 23: *Segmentation with far obstacles.*

Figure 24: *Segmentation with far obstacles, other example.*

Figure 25: *Highway road segmentation without obstacle.*

Figure 26: *Low contrast road segmentation.*

Figure 27: *Curved road segmentation*

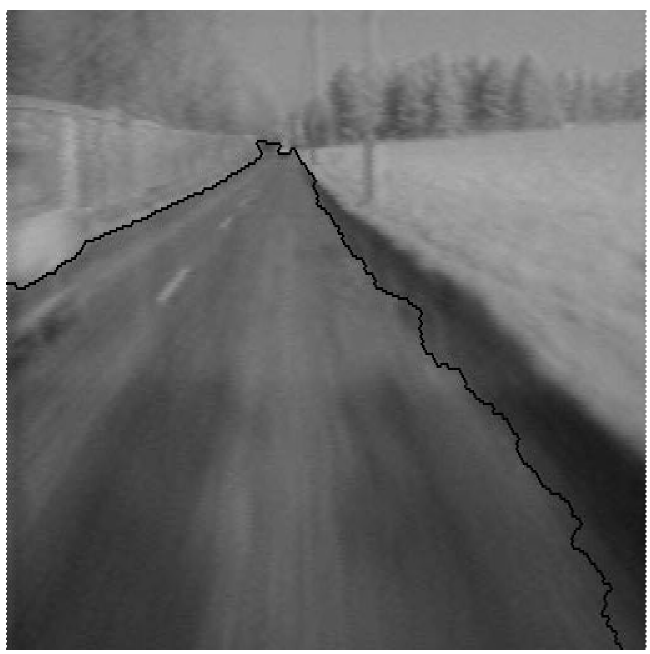


Figure 28: *Low contrast secondary road segmentation.*

Figure 29: *Scene with shading.*

6 CONCLUSIONS

These first results need further validation. The biggest difficulty is false detection due to the shadows, because they are considered as obstacles. In that last case, complementary information given by telemetry or by stereovision is needed.Another possible way of exploration would be color processing. This could enhance edge detection but with an increase of the processing time. In order to reduce this computation time, watershed algorithms using parallel processing and different representations of an image are elaborated. Detected markers could also be used in obstacles following in a sequence of images.

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