Vision-based lane boundaries following for autonomous vehicle guidance

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Abstract *This paper proposes a technique for lane boundaries detection and following, which can be used in a driver assistance system. This technique is destined only to painted road with slow curvature. Then, a linear model is used to obtain robust information about vehicle position and orientation compared to the road boundaries. Based on the gray level images our approach uses the Radon transform to extract the white lane markers with exploiting the contrast between these markers and road surface. To ensure robustness to the lane following process, we assume a temporal correlation between the successive images. Experimental results indicate that the proposed approach can fit lane boundaries in the presence of several image artifacts, such as sparse shadows and lighting changes.*

Introduction

The road accidents are currently among the principal causes of death in the world. They occur in various situations, and for various reasons. A particular type of these accidents is called Single Vehicle Road Departure (SVRD) that involves a single vehicle, which departs the road and then impacts something such as a tree or a bridge abutment. The degradation of driver performance during a long driving task can be a direct cause of SVRD. A fatigued or impaired driver during highway driving is an obvious example. Recently driver distraction (e.g., cellular phones, navigation systems) has received considerable attention. So, a great deal of research in the domain of transport systems has been conducted to improve the safety conditions by the partial automation of some driving tasks. Among these tasks, the lane recognition take an important part in each drive assistance system and autonomous vehicle, which provides information such as lane structure and vehicle position relative to the lane.

Thanks to the great deal of information it can deliver, computer vision become a powerful means for sensing the environment and has been widely used in lane boundaries detection and following. A common theme among many previous lane trackers is the use of lane markers as the primary feature for tracking and consequently there are a number of techniques for lane marker extraction.
The General Obstacle and Lane Detection system (GOLD) used in the ARGO vehicle at the University of Parma exploits a flat road assumption to help simplify the problem of lane tracking (M. Bertozzi, A. Broggi, 1998). The system transforms stereo image pairs into a common bird's eye view using an inverse projective mapping and uses a pattern matching technique to detect lane markings on the road.

The group at the University of Michigan has produced two novel contributions to the field of lane tracking: LOIS and LANA (Kreucher et al, 1998; Kreucher & Lakshmanan, 1999), where a parametric family of deformable templates is used to identify lanes, with the likelihood measure identifying how well a particular parameterization matches the observation. Moreover, a prior model constrains the possible locations of the lane based on the lane location from the previous frame.

Pomerleau and Jochem propose in (Pomerleau and Jochem, 1996) a RALPH system, used to control the lateral position of an autonomous vehicle. It is based on the processing of the image portion corresponding to road about 20-70m ahead the vehicle, depending on the vehicle's speed and obstacles presence. It uses a matching technique that adaptively adjusts and aligns a template to the averaged scanline intensity profile in order to determine the lane's curvature and lateral offsets.

A lane detection algorithm destined to painted or unpainted road has been proposed by Ran et al (Ran & Xianghong Liu, 2000). In this algorithm color cues were used to conduct image segmentation and remove the shadow of the road. Assuming that the lanes are normally long and smooth curves, then its can considered as straight lines within a reasonable range for vehicle safety. The lanes were detected using Hough transformation applied to the edge image. In the lane following phase, a temporal correlation is assumed between successive images.

Other lane detection and following approach based on Hough transform is proposed by McDonald and Markham in (Mc Donald, 2001). Specifically this algorithm is based on automatic extraction of road position during motorway driving scenarios. Geometrics constraints are assumed on the road contours in order to reduce the Hough space search. Moreover, temporal constraints were assuming in the form of a dynamic focus-of-attention windows in Hough space. Since the Hough transform works on binary valued images, it was necessary to combine a thresholding and edge detection operator.

The vision system to find real lanes boundaries must be able to operate robustly under a wide variety of environmental conditions including large amount of scene clutters. The clutters can be due to shadows, surface wears, tire skid marks, oil drops, occlusion by other vehicles, etc. It is difficult to select true edges corresponding to real lanes boundaries while removing the edges corresponding to irrelevant clutters. The reviews of the most advanced approaches on road following and detection are presented in (Bertozzi et al 2002; Kastrinaki et al, 2003).

This paper presents a vision based lane boundaries detection and following algorithm destined to marked road, which is robust enough in presence of shadow conditions. The proposed system must automatically detect and track the white lane boundaries. Some hypothesis, are established on road structure. The vehicle is supposed to move on a flat and straight road or with slow curvature. Hence, the lane boundaries are assumed locally parallel, and, the lane markings can be described by two parallel straight lines in the front of the vehicle. Generally, even in presence of shadows or lighting changes, the lane markings and the road asphalt remain always contrasted. Using this characteristic, we propose to use the Radon Transform computed on specific windows to extract a pair of segments delimiting the lane markings. Compared to our preceding works (Nourine et al 2004), this approach is more robust and more precise on the boundaries localization.

Proposed road model

Several vision-based road detection and tracking systems uses a model in order to do reliable recognition. The use of models simplifies the detection process, by limiting the search area and restricts the parameters model intervals. However, many of model-based systems establish some constraints on this environment in order to have a unique solution in the boundaries detection process. In our case, we suppose that the vehicle circulate on a road where the lane boundaries are marked by white bands painted on the roadway, and we make following constraints on the road structure:

• The vehicle is moving on a flat straight road or with slow curvature.
• The lane boundaries are assumed locally parallel.
• The lane boundaries are continuous in the image plane, which implies their continuity in the physical world.
• We suppose that the displacement of the vehicle is "regular", without abrupt gesture, what implies a temporal correlation between two successive images.

$$\rho_l = x\cos\theta_l + y\sin\theta_l \quad \text{and} \quad \rho_r = x\cos\theta_r + y\sin\theta_r \quad ; \qquad (1)$$

where (θ_l, ρ_l) and (θ_r, ρ_r) correspond respectively to the left and right lane boundaries and (x, y) is pixel on the corresponding line.

In order to establish the position and the orientation of the vehicle compared to the road boundaries we propose to calculate four parameters (fig.1): vanishing point (P), vehicle orientation (ϕ), lateral offset (δ) and lane width(λ).

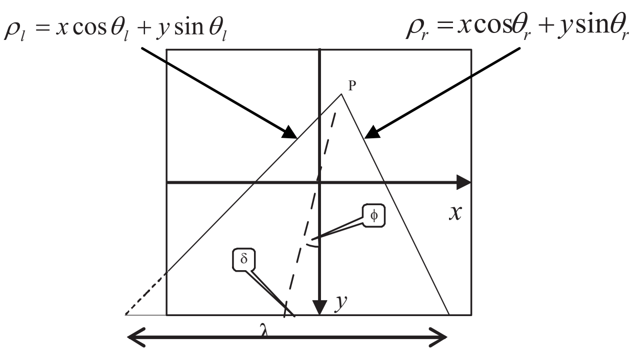


Figure 1.
Road model

Based on these assumptions, the area of current lane in front of the vehicle can be described by two parallel straight lines. The perspective projections of these parallel lines to the image plan are not parallel but converge to a vanishing point.

So, the lane boundaries can be approximated by two straight lines (Eq.1) as showed in fig.1:

The lane boundaries detection and following strategy proposed in this paper place in two phases. At the beginning, the vision system executes an initial phase that analyses the first acquired image with some assumptions made on road and on the vehicle position and orientation. This phase allows vision system to initialize the following phase, which is performed on the successive images in order to follow up on lane boundaries. We present below a description of these two phases.

Initial lane boundaries detection

In the initial phase the first image acquired by the camera is processed to extract automatically the two (left and right) lane boundaries. We assume that the vehicle is initially located in a straight portion of the road, centered inside the lane, oriented approximately in the same way to the lane axis. Moreover, we suppose that the lane markings are visible in the inferior half of the image as shown in fig.2. Thus, the left and right boundaries are required respectively in the left (WL) and right (WR) windows.

The aim is to calculate the parameters of respectively the left and right boundary such as defined by Eq.1. Exploiting the knowledge about the acquisition parameters, the vision system can predict the lane boundaries orientation on the image plan. We present below the algorithm of the left lane boundary detection. The similar algorithm is used for the right boundary.

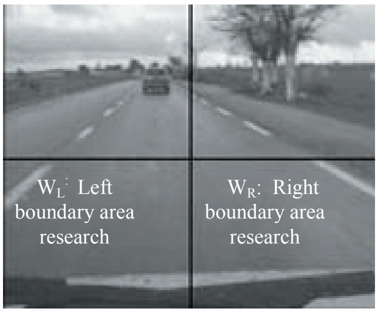


Figure 2. Typical initial image

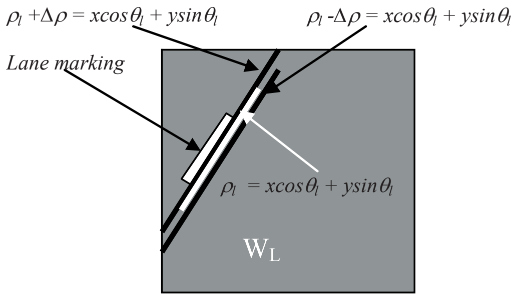


Figure 3. Left bound-ary charac-teris-tics

Let consider *I(x,y)* as the acquired greyscale image. In fig.3, we present a description of the left boundary position in windows W_L. We consider that this boundary is a straight line tangent to the interior limit of the lane markers, described by the parameter (θ_l, ρ_l). Moreover, this line is located between two lines, such as one passes across white markings of the road and the other passes on dark asphalt, described respectively by $(\theta_l, \rho_l + \Delta_\rho)$and $(\theta_l, \rho_l - \Delta_\rho)$.

In this initial phase, we first compute $[\theta_{min}, \theta_{max}]$ as the predicted search domain of the orientation parameter θ_l (for the left boundary), who must be extracted in W_L. On the other hand, no explicit constraints were placed on the distance parameter ρ_l. Nevertheless, its research domain depends on the image plan size. Let $[\rho_{min}, \rho_{max}]$ the estimated search domain of ρ_l in windows W_L.

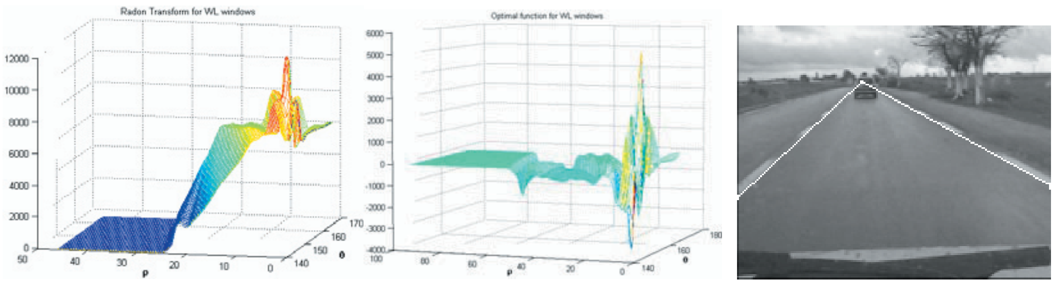
Applying the Radon transform to W_L results in a 2D function $R(\theta, \rho)$ that represents the sum of grey levels of all points in the image satisfying the linear equation $\rho = x\cos\theta + y\sin\theta$ (Eq.2), and showed in fig.4.a. The large values around the pick correspond to lines that cross marks in the road. The motivation of the Radon transform use instead of the Hough transform is the possible application of the Radon transform directly to the grey levels image ([1]Nourine et al 2004).

$$R(\theta,\rho) = \sum_{x,y} I(x,y) \quad , \quad \theta \in [\theta_{min}, \theta_{max}] \text{ and } \rho \in [\rho_{min}, \rho_{max}] \quad ; \qquad (2)$$

As described above, we search a line which is a transition between the white lane marking and the dark road surface (see fig.3). To obtain that we propose to compute from the already calculated Radon transform, a new function noted $F(\theta, \rho)$, called performance measure and defined by Eq.3. Thus, the optimal solution $(\theta_{l(0)}, \rho_{l(0)})$ for the left boundary according to F corresponds to its local maximum as defined by Eq.4 and shown in fig.4.b. The result of the lane boundaries detection in the first image (time=0) is indicated in fig.4.c, and the corresponding parameters are described by the vector $\Omega_0 = (\theta_{l0}, \rho_{l0}, \theta_{r0}, \rho_{r0})$. Based on these parameters we compute the road model noted $M_0 = (P_0, \phi_0, \delta_0, \lambda_0)$.

$$F(\theta,\rho) = R(\theta,\rho+\Delta\theta) - R(\theta,\rho+\Delta\rho) \quad , \quad \theta \in [\theta_{\min}, \theta_{\max}] \text{ and } \rho \in [\rho_{\min}+1, \rho_{\max}-1] \quad ; \qquad (3)$$

$$F\left(\theta_{l(0)}, \rho_{l(0)}\right) = Max\left(F(\theta,\rho)\right) \quad , \theta \in [\theta_{\min}, \theta_{\max}] \text{ and } \rho \in [\rho_{\min}+1, \rho_{\max}-1] \quad ; \qquad (4)$$



(a) (b) (c)

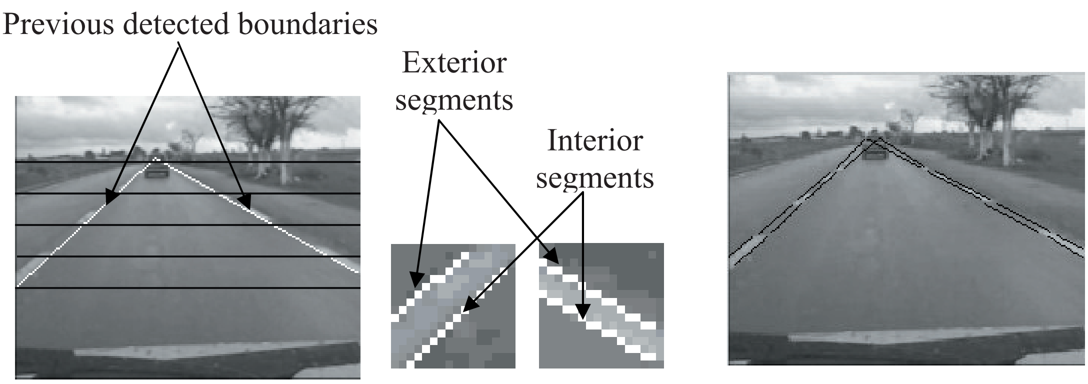
Figure 4. (a) Radon transform (b) Performance measure (c) Detected lane boundaries

Lane boundaries following

In the following phase, the system needs to update the lane boundaries detection for the subsequent images. In the initial phase the lane boundaries research was limited on the lower half of the image since we suppose that they are clearly visible there. However, this assumption is generally not valid on all subsequent images. So, in the following phase each new acquired image is divided into several small horizontal regions noted Aj (j=1..N), according to the previous result as showed in fig.5.a. The lane boundaries are then locally extracted on each region by detecting the line segments delimiting the lane markers. Like in initial phase the linear segments detection is based on Radon transform. However, it exploits the preceding results to limit the image area research and parameters intervals.

Local lane boundary detection

In each horizontal region, two windows WL and WR are selected. We assume that if a window (WL or WR) contains a white lane marking, then it will be delimited by two straight segments as showed in fig.5.b. These segments are located respectively, on the interior and exterior side of the lane markers. Only the left lane segments detection algorithm is described next. The right lane segments are extracted in a similar way.



(a) **(b)** **(c)**

Figure 4. (a) Subdivided Image (b)Search windows (c)Extracted segments

Let denote $\left(\theta^{j}_{l(t-1)}, \rho^{j}_{l(t-1)}\right)$ the left lane boundaries parameters extracted at time t-1, on a selected horizontal region A_j. The Radon transform noted $R(\theta, \rho)$ is computed on the corresponding window W_L with Eq.5, followed with a performance measure $F(\theta, \rho)$, as defined in Eq.6.

$$R\,(\theta,\rho)=\sum_{x,y} I(x,y), \quad \theta\in\left[\theta^{j}_{l(t-1)}-\Delta\theta, \theta^{j}_{l(t-1)}+\Delta\theta\right] \& \;\; \rho\in\left[\rho^{j}_{l(t-1)}-\Delta\rho, \rho^{j}_{l(t-1)}+\Delta\rho\right] \; ; \tag{5}$$

$$F(\theta,\rho)=R_l(\theta,\rho+\Delta\theta)\text{-}\mathrm{R}_l(\theta,\rho\text{-}\Delta\theta) \; ; \tag{6}$$

The performance measure will be characterized by a peak and a trough such as showed in fig.4.b, especially when W_L contains a white marking. Thus, we consider that the maximum of the performance measure determines the parameters $\left(\theta^{jI}_{l(t)}, \rho^{jI}_{l(t)}\right)$ of the interior segment (Eq.7). On another side, the minimum of this function corresponds to the external segment represented by the parameters $\left(\theta^{jE}_{l(t)}, \rho^{jE}_{l(t)}\right)$ obtained by Eq.8.

$$F\left(\theta^{jI}_{l(t)}, \rho^{jI}_{l(t)}\right)=Max\left(F_l(\theta\;,\rho\;)\right) \; ; \tag{7}$$

$$F\left(\theta^{jE}_{l(t)}, \rho^{jE}_{l(t)}\right)=Min\left(F_l(\theta,\rho)\right) \; ; \tag{8}$$

A similar process is applied for the right white lane marking in the same sub-region. Thus, in each sub-region two pairs of segments are extracted corresponding to the left and right lane boundaries, such as showed in fig.5.c.

Suppression of no representative segments

In each analyzed region, the segments must check two requirements. Each pair of segments in the image must represent two parallel segments on the roadway. So, they must converge towards a vanishing point. Moreover, each pair of segments must necessarily delimit a white marking.

Then, we first eliminate the segments which not correspondent to parallel lines on the roadway. Let take $\left(\theta^{jI}_{l(t)}, \rho^{jI}_{l(t)}\right)$ and $\left(\theta^{jE}_{l(t)}, \rho^{jE}_{l(t)}\right)$ as the parameters of respectively the interior and exterior segments extracted from the left windows on a region A_j at time t. These two segments represent two parallel lines in the roadway if $\theta^{jI}_{l(t)} > \theta^{jE}_{l(t)}$. A pair of segments extracted on the right window, characterized respectively by $\left(\theta^{jI}_{r(t)}, \rho^{jI}_{r(t)}\right)$ and $\left(\theta^{jE}_{r(t)}, \rho^{jE}_{r(t)}\right)$, must verify $\theta^{jI}_{r(t)} < \theta^{jE}_{r(t)}$ to represent two parallel straight lines in the roadway.

Furthermore, we consider the pixels which do not belong to the white marking as false edges pixels. To detect them, we propose to analyze the gradient distribution function calculated on the extracted segments. The edge pixels are searched which are given by local maxima of gradient magnitude in gradient direction. Let denote G_x and G_y the components of the gradient magnitude computed in the x and y directions for a pixel (x, y).We propose the Sobel operator to compute these components (Pratt, W.K. 1991). Then, the moment matrix

$$M=\begin{pmatrix} \mu_{2,0} & \mu_{1,1} \\ \mu_{1,1} & \mu_{0,2} \end{pmatrix} \; ; \tag{9}$$

is computed at this pixel with the moments

$$\mu_{k,l}=\frac{1}{N^2}\sum_{i=-n}^{n}\sum_{j=-n}^{n} G_x^k(x\;+i,y\;+j)G_y^l(x\;+i,y\;+j) \text{with k,l}=0,1,2 \text{ and } \mathrm{N}=2\mathrm{n}+1 \; ;$$

The idea is to use the eigenvalues and the eigenvectors of the moment matrix M to determine if the pixel (x, y) is a true edge or not. If both eigenvalues are small, the corresponding image region (region of used mask) is homogenous. In inhomogeneous regions, both eigenvectors have eigenvalues of a significant magnitude. On edge structures one eigenvalue is significantly greater than the other. Thus, each pixel whose corresponding eigenvalues are very different is considered as an edge pixel, the others pixels are eliminated. The fig.6.b presents the result of false edge elimination applied to fig.6.a.

Finally, a polygonal approximation is computed on extracted interior segment to determine the parameters of left and right lines adjusting the lane boundaries, as showed in fig.6.c.

(a) (b) (c)

Figure 6.
(a) False segments suppression
(b) no-maxa pixels suppression
(c) Extracted lane boundaries

Experimental results

The proposed lane detection/following algorithm was implemented in Dell Pentium IV 1.8 GHz computer by using Matlab 7. It was tested on several video sequences (on off line) containing several conditions, such as the varying illumination, presence of shadows and weak painting of the lane markers. The video sequences were obtained at 30frames per second, with resolution 176 x 144 pixels.

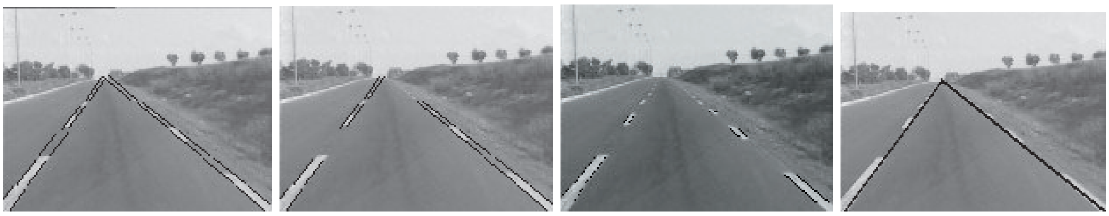
The first video sequence (fig.7) illustrates a road characterized by quite visible white markers. In this road type the detection/following module is very strong. In top there are the stages of the detection process applied to an image. The sequence in bottom shows the results of the lane boundaries following in some next images.

The second sequence shows a road where shadows caused by trees or other vehicles are projected on road surface. Such as we described it in the introduction, the principle of our approach is based on the strength of the Radon transform to detect the linear elements even in the presence of noise. Thus, as showed in fig.8 and fig.9, the lane boundaries are extracted and followed in spite of shadows presence.

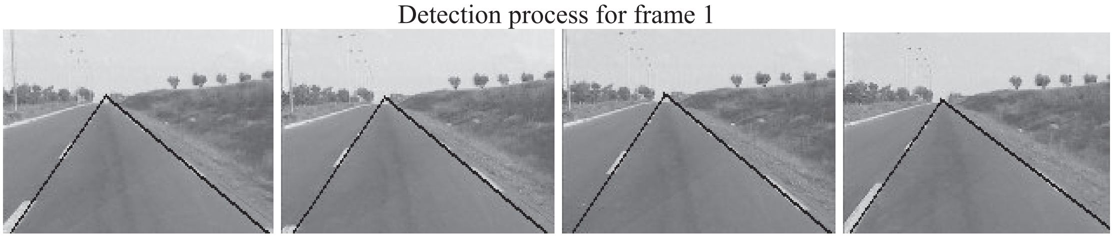
The most critical situation that we met in certain sequences is the lack of the lane markings on image research zones (W_L, W_R). Therefore, the detection of white markers fails, which makes impossible the estimate of the lanes boundaries. Based on the assumptions made on the road structure and temporal correlation between successive images, we take the previous result (in precedent image) and we start again the process on the following image. If the process still fails, the system stops

Conclusion

In this paper, we present a low-cost lane detection algorithm based on video sequences taken from monocular vision-system mounted on a vehicle. Real time lane detection and following system is an essential module of an object detection and recognition system for crash warning and avoidance. The vehicle is supposed moving on a flat and straight road or with slow curvature. Hence, we consider the lane boundaries as straight lines. The basic idea is that the complete processing of each image can be avoided using the knowledge of the position of lane boundaries in the previous ones. The proposed lane detection and following can be applied only in painted road. The lane boundaries were detected using the localized Radon transform. The proposed approach has been tested on video data, and the experimental results have demonstrated a fast and robust algorithm. A parallel programming will obviously reduce the computing time.

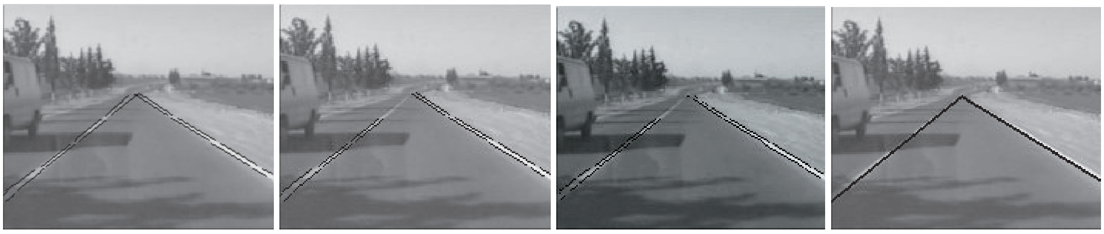


Detection process for frame 1

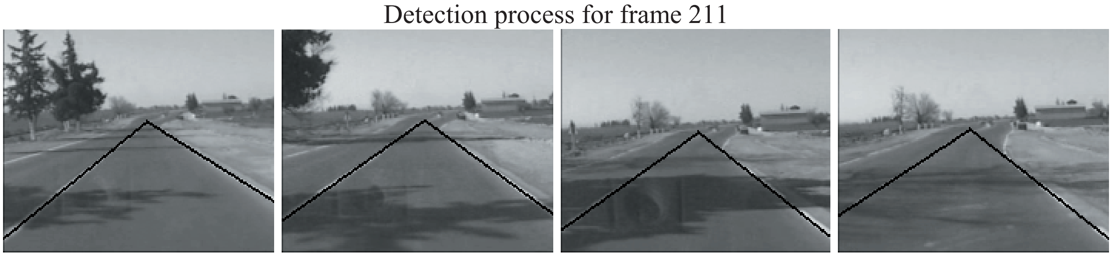


frame 5 frame 8 frame 14 frame 28

Figure 7. Typical road with markers

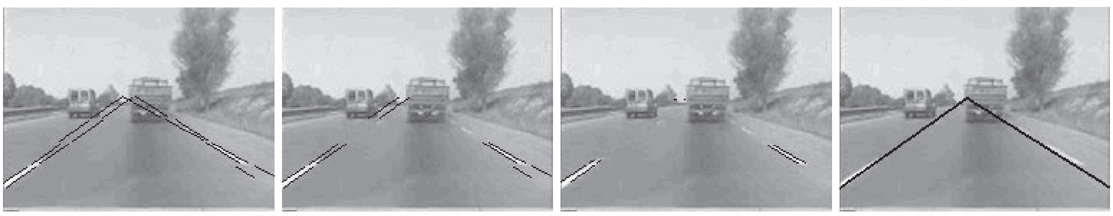


Detection process for frame 211

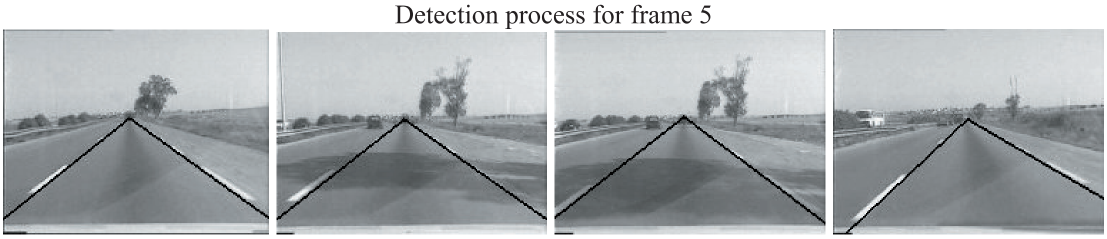


frame 284 frame 323 frame 347 frame 360

Figure 8. Road with shadows presence



Detection process for frame 5



frame 50 frame 197 frame 199 frame 390

Figure 9. Motorway sequence

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