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DEVELOPMENT OF LATERAL COLLISION AVOIDANCE SYSTEM FROM REARVIEW MIRROR IMAGES PROCESSING

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ABSTRACT

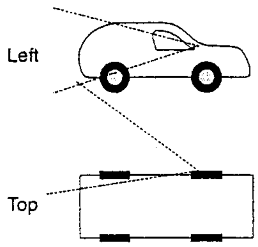
This paper presents a vision-based lateral collision avoidance system, which makes use of rearview mirror images to eliminate blind zones on the left of the vehicle. Using the image sequences given by a camera installed near the left lateral rearview mirror, the system is able to detect potential obstacles thanks to a road line detection method, a perspective-compensating resampling process and motion estimation.

1. INTRODUCTION

Significant progress has been achieved in the domain of computer vision for support of road vehicle drivers in order to improve the road vehicle guidance and safety. For example, European EUREKA project PROMETHEUS (PROgraMme for a European Traffic with Highest Efficiency and Unprecedented Safety, 1986-1994), and in Japan and in the USA, the Intelligent Vehicles Highway System (IVHS). Recently, the technologies that provide for collision avoidance during overtaking have attracted considerable attention [1].

Many accidents are caused by a lateral collision with a vehicle driving on the left lane which has not been seen by the driver before he overtakes. The field of view in the left rearview mirror is not wide enough, and potential obstacles may be hidden in the dead angle. To solve this problem, most of today's vehicles have come to be equipped with a double rearview mirror eliminating blind zones. One of the parts of the mirror must be adjusted in a particular way, but unfortunately, this adjustment is difficult to verify and maintain. Another way to eliminate dangerous blind spots is to install a wide internal rearview mirror giving a better view of all surrounding traffic (300% more than conventional mirrors).

This paper presents a lateral collision avoidance system based on rearview mirror images processing. Obstacles are detected by a motion analysis algorithm using the image sequence supplied by a video camera mounted on the left rearview mirror. The field of view of this camera has been adjusted in order to reduce to a minimum the dead angle. Figure (1) shows a camera looking at the rearview scene.



(a) Camera orientation

(b) Rearview image

Figure 1: Watching the rearview scene

The following section presents the overall structure of the system, while section 3 discusses the processing for road line recognition. Section 4 describes the computing architecture of iterated extended Kalman filter for the prediction of parameters of the road model and vehicle orientation based on line detection. Section 5 presents the relevance of image resampling for motion analysis. Section 6 shows the experimental results obtained by a simulation. Finally, section 7 ends the paper with some concluding remarks.

2. LATERAL COLLISION AVOIDANCE SYSTEM

We know that line detection is always used in various driver assistance systems. It will also be used in our approach. Let us notice that the image sequence implicitly identifies the recent path taken by the vehicle. This means that we can detect lane boundaries and obtain vehicle position relative to the center line with great precision. The prediction of road model and vehicle

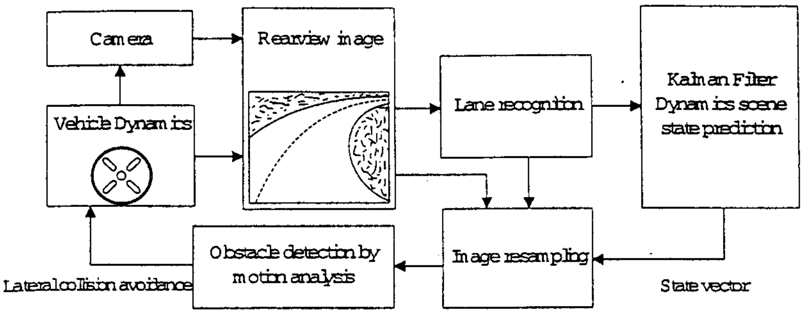


Figure 2: Lateral collision avoidance system

orientation parameters based on the lane detection is calculated through an iterated extended Kalman filter. After calculating the road model and vehicle orientation parameters, the images are resampled in order to remove the perspective effect. Then, a motion analysis is performed by a Time Delay Neural Network (TDNN) proposed by Ambellouis [2]. This overall strategy is shown in Figure (2).

3. ROAD LANE RECOGNITION

3.1 Segmentation

Lane detection is a very delicate task in outdoor scenes with sometimes disturbing heterogeneous light conditions and shadow effects. For a reliable lane detection, a detection method called "peak and valley" [3] is applied, which has a strong robustness for picking up the lanes [1].

Here the procedure "peak and valley", which is used to detect the road line, relies on an analysis of the first derivative of the grey level profile. If we assume that the pixels belonging to a white line have a grey level value higher than their left and right neighbors, the detection becomes a reliable determination of horizontal black-white-black transitions. We analyse the grey level profile of each lines of the image, and use its variations to recognize the white lines. In presence of a white line, there exists simultaneously a maximum and a minimum in the resulting derivative profile : a peak and a valley. This is illustrated on figure (3).

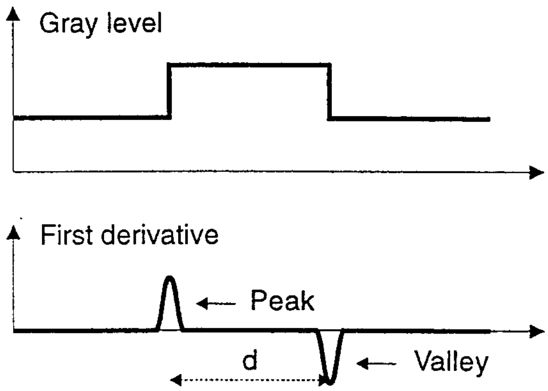
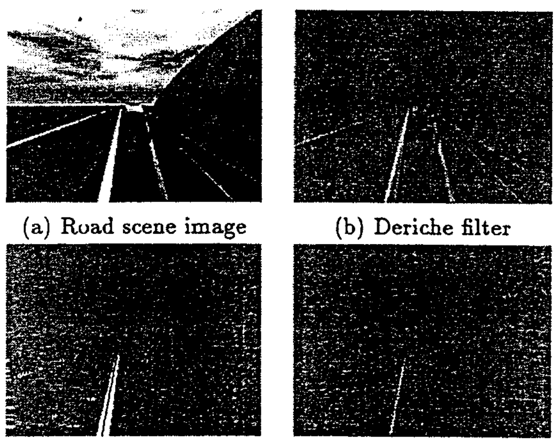


Figure 3: Peak and Valley method

The recognition process allows us to measure the width between these two extrema, which depends on the road lane width. As we know, in the real-world coordinate system, the width of the white line is constant and well known, so we can set a threshold zone to filter out noise and to guarantee that the area between the two extrema corresponds to a white line.

3.2 Reconstruction

The method stated above has been extended to the general case of lane detection with two steps : feature extraction and reconstruction. In the first phase, an input image processed with a horizontal edge detection filter (Deriche filter) is analyzed by the peak and valley method, so an output image containing all of the peaks and valleys is given. The next phase deals with the binary image processing and noise filtering which uses an approach based on comparison, order etc. in order to reconstruct the lane. Figure (4) illustrates this process.



(a) Road scene image (b) Deriche filter (c) Detection result (d) Line reconstruction

Figure 4: White line detection and reconstruction

The road model is usually constructed of lines, circles and clothoid curves. By means of a differential geometry method, we set up a road model characterizing the dynamic relationship between the local road curvature

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C, the vehicle position x_0 and the angle ψ between the optical axis and the lane tangent.

4. UPDATING THE ROAD MODEL

4.1 Task description and variables definition

We have defined the dynamic scene system *state vector* x including the above mentioned vehicle posture parameters and lane structure parameters as below :

$$x = [C, x_0, \psi]^T, \tag{1}$$

where C denotes the local road curvature, x_0 the distance between the vehicle and the line center and ψ the angle between the optical axis and the lane tangent.

In order to track these variables dynamically, we must develop a recursive predictor estimating them by processing image sequences successively in real time. As we know, the *Kalman filter* is likely to have applications throughout computer vision as a general method for integrating noisy measurements [4], [5], [6], [7]. The behavior of a dynamic system can be described by the evolution of a set of variables, called *state variables.* In practice, the individual state variable of a dynamic system cannot be determined exactly by direct measurements; instead, we usually find that the measurements that we make are functions of the state variables and that these measurements are corrupted by random noise. The system itself may also be subjected to random disturbances. It is then necessary to estimate the state variables from the noisy observations.

The values observed and measured in the image are the coordinates (x_e1, y_e1), (x_e2, y_e2), (x_e3, y_e3) of three points in the center of the white line detected as shown in Figure (4). They are fed into a Kalman filter in order to update the state vector x characterizing the road curvature and the current camera position and orientation with respect to the lane (equation (1)).

4.2 Basic relationships from differential geometry

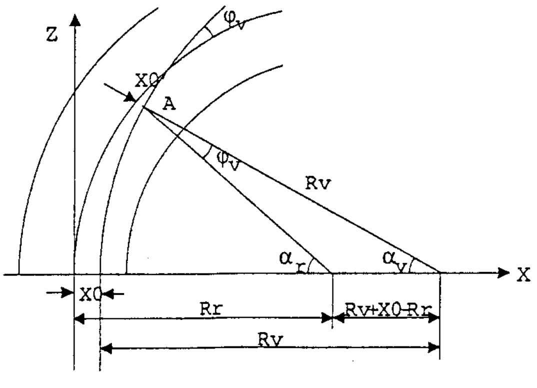


Figure 5: Local coordinate system

Without loss of generality, we can adopt a common shape model in tracking the vehicle position as the vehicle moves at a certain velocity V along the road with a road curvature radius R_r. Figure (5) shows a road segment with the local coordinate system where Z and X are respectively defined as the direction of the length and the width of the road, in which the origin of the coordinate system corresponds to the center of the lane. R_r and R_v are respectively the radius of curvature of the road and the vehicle trajectory. A is a point on the curve of the road and ψ is the tangent direction angle to the curve at A. x_0 and x_0' denote the distance between the vehicle and the center of the lane at two moments $t1$ and $t2$ $(t2 - t1 = t)$ which corresponds to the sampling time of the image sequence. Therefore the following relations hold :

$$\begin{aligned} Vt &= R_v \alpha_v, \\ Vt &= R_r \alpha_r. \end{aligned} \tag{2}$$

In the case that ψ, α_v and α_r are very small, we obtain the expression :

$$x_0(k+1) = R_r(k) - \sqrt{(R_r(k) - x_0(k))^2 + \psi(k)R_r(k)V(k)t)} \tag{3}$$

The *extended Kalman filter* is a version of the Kalman filter based on a linearization of the nonlinear observations and the dynamics function at the current model parameter values [8]. As mentioned above, in our application, the state equation describing the dynamics of the state vector x is nonlinear, so the extented Kalman filter is used. We adopted the extended Kalman filter to update the parameters characterizing the current camera position and orientation, and the geometry of the road.

4.3 Iterative extended Kalman filter

The *iterative extended Kalman filter* provides better performance than the basic extended Kalman filter, especially in the case of significant nonlinearity in the measurement function. This is because when the newest state estimate is generated after measurement incorporation, this value can serve as a better state estimate than the old one for evaluating the measurement update relation. Then the state estimate after measurement incorporation can be recomputed iteratively if desired.

An evident feature of the proposed recursive method is that, by means of some simple geometric calculations, we can indirectly and approximately determine the *measurement vector* z which is expressed as :

$$z = [C_m, x_{0m}, \psi_m]^T. \tag{4}$$

Based on the approximate measurement vector z, the state vector x described above can be updated by the extented Kalman filter. The outline of the procedure follows 6 successive steps.

1. Initialization of the predicted state vector x_0, of the covariance matrix P_0, of the system noise matrix Q and the measurement matrix R.
2. By a method of white line detection and road reconstruction, the coordinates of three points in the center lane on the image are computed.
3. The measurement vector z is calculated based on these three points.
4. The state vector x is updated by the extended Kalman filter
   (a) Update Kalman gain K.
   (b) Update estimated state vector x.
   (c) Update the covariance matrix of estimated state vector P.
   (d) Update the predicted state vector by its non-linear function.
   (e) Update the covariance matrix of the predicted state vector.
5. Step 4 is repeated several times until the extimated variables have been updated with sufficient precision. Generally speaking, the number of iterations for *Iterative Kalman Filtering* is set to 3 or 5.
6. Obtain a new road image; return to Step 2.

Results of this algorithm are given in section 6.

5. OBSTACLE DETECTION

Obstacle detection is performed by motion estimation on image sequences in which the perspective effect has been removed. In [1] and [9] we introduced the procedure for image resampling and motion estimation, and we verified the necessity of the resampling process to obtain a precise determination of the relative velocity of the detected vehicles. The chosen motion analysis procedure has proved to be well suited to the problem of relative speed determination.

To meet the requirements of the motion estimation algorithm, it is necessary to remove the distortion due to the perspective effect in the images. We apply a resampling procedure to each image of the sequence. Moreover, this allows a significant reduction of the amount of data to be processed during the following steps, and greatly increases the execution speed of the algorithms. The parameters required by the resampling procedure are given by an analysis of the optical system and an estimation of the geometry of the road.

Figure (6) shows a series of rearview images acquired aboard a vehicle driving on a turning highway. These images have been sampled under non ideal conditions : the high luminosity level has created a saturation of the grey level in the top part of the images. In this sequence, we can see a car which overtakes our own vehicle.

In figure (7), the resampling points are defined assuming that the road is straight. Figure (8) shows the grid used for removing the perspective effect based on the results of road detection : the radius is 1000m and the location of camera is 1m to the right of the road axis.

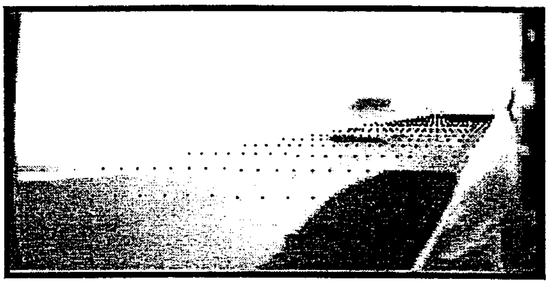


Figure 7: Grid for a straight resampling

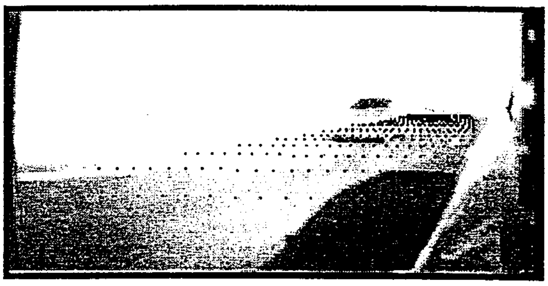


Figure 8: Grid for a curved resampling

Figure (9) presents the resampled images of the sequence shown in figure (6). In each small image, the axis of the road is horizontal and the part close to our vehicle is on the left side. The images of the first series (figure (9(a)) are obtained after a resampling with a straight grid, whereas the images of the second series (figure (9(b)) were resampled with a curved grid.

6. EXPERIMENTAL RESULTS

6.1 Changing course on a straight way

An example of the proposed method for estimating the *state variable* presented in section 4 is shown in the following simulation experiment. A synthetic image sequence, containing 45 successive frames and showing a typical road scene, is used to evaluate the whole detection process when a vehicle changes course (see Figure (10)). In this synthetic image sequence, the road parameters are defined as follows : the width of the white line is $0.14m$, the width of the road is $3m$, the

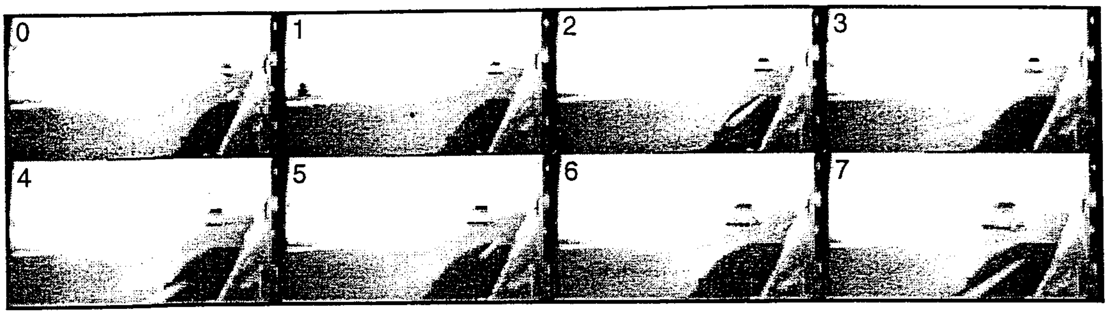
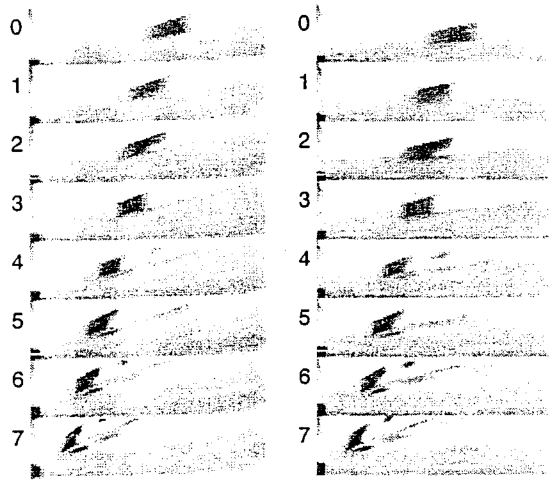


Figure 6: Rearview mirror image sequence



(a) Straight grid (b) Curved grid

Figure 9: Resampled sequence

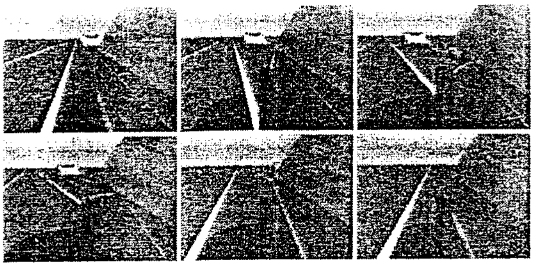


Figure 10: The scene of changing course

road curvature is 0.00001, that is to say the road is almost straight. The initial distance between our vehicle and the central white line is $0.4m$. Moreover, our vehicle will change course from right to left by an approximately sinusoidal path.

The initial values of the estimated state vector x_0 and covariance matrix P_0 are :

$$\begin{aligned} x &= [0.00001, 0.2, 0]^T, \\ P_0 &= diag(0.01^2, 0.01^2, 0.01^2). \end{aligned}$$

System noise covariance matrix Q and measurement noise covariance matrix R are set to be :

$$Q = diag(0.4^2, 0.5^2, 0.871^2),$$

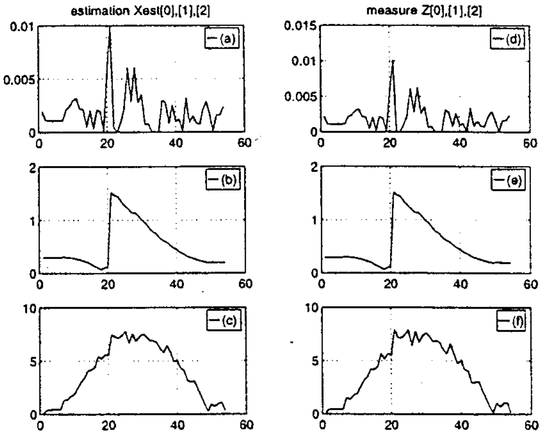


Figure 11: Estimated results

$$R = diag(1.0^2, 1.0^2, 4.0^2).$$

The results of applying the procedure to the simulated images are shown in Figure (11). The diagrams on the left show the estimated state variables x_{est} calculated by the iterative extented Kalman filter, and those on the right show the measurement variables z calculated. It is clear that the estimated results agree well with the real state variables. We notice that in the second row of this figure((b) and (e)), there is a sudden change in x_0 and x_{0m} plots. This is because when our vehicle has crossed the central line, this line becomes invisible, and the camera then follows the next line on the left.

Figure (12) compares the true value of the third state variable ψ, during the process of vehicle course change, to the value estimated by using iterative extended Kalman filter presented in section 4.2, over a sequence of 54 images.

6.2 Overtaking on a straight road

Overtaking is considerd as a special case of lateral collision avoidance. In this case, the line being detected is largely occluded by the overtaking vehicle. Therefore, the main task is to determine a reference line or road boundary depending on the context. In Figure (13), on the left, an example of difficulty is shown by a rearview

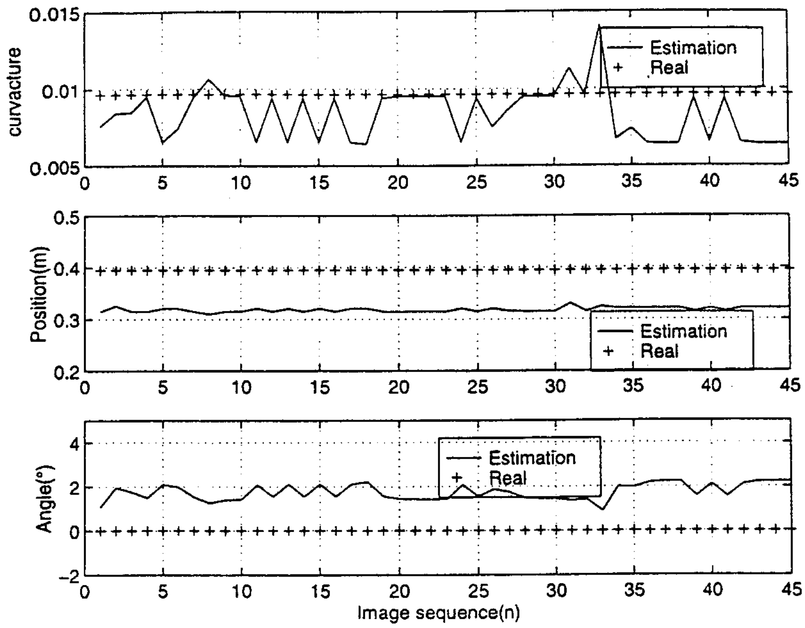


Figure 15: Estimated results

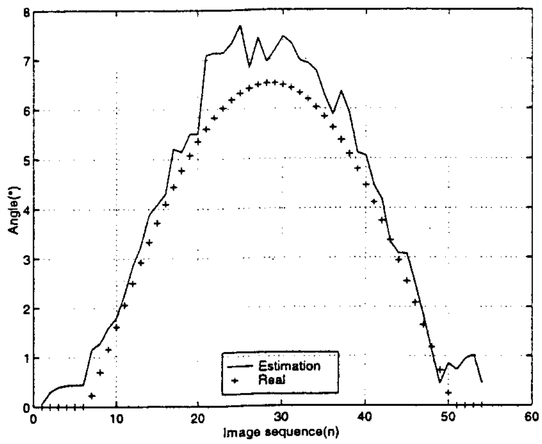


Figure 12: Change of the angle ψ over time

image sequence. It details the situation in which our vehicle is overtaken by another one and it is almost impossible to recognize the line. On the right hand, it is shown that this type of difficult situation can be handled with a road reconstruction technique presented in section 3.

6.3 Turning on a curved road

Figure (14) shows an image in which our vehicle moves along a curving road. The curvature radius of the road is about $100m$, the distance between the vehicle and the center line is about $0.4m$ and the angle ψ between the optical axis and the line tangent is 0. Figure (15) displays the true *state variable* values (as used in the simulation) against the ones estimated by the iterative extended Kalman filter discussed in section 4. The other test conditions and parameters are the same in section 6.1.

7. CONCLUSION

This paper presented an approach to develop a lateral collision avoidance system based on rearview images processing. Our approach allows :

- to reconstruct reliably the road lines,
- to update the road model in a dynamic scene by iterated extended Kalman filter from image sequences,
- to detect lateral obstacles by image resampling and motion analysis.

The proposed scheme for a rearview analysis system, which is a very challenging and very promising topic in the domain of driver assistance systems, has been researched deeply. An extension to implement the whole lateral collision avoidance system on a vehicle is now under development.

ACKNOWLEDGEMENTS

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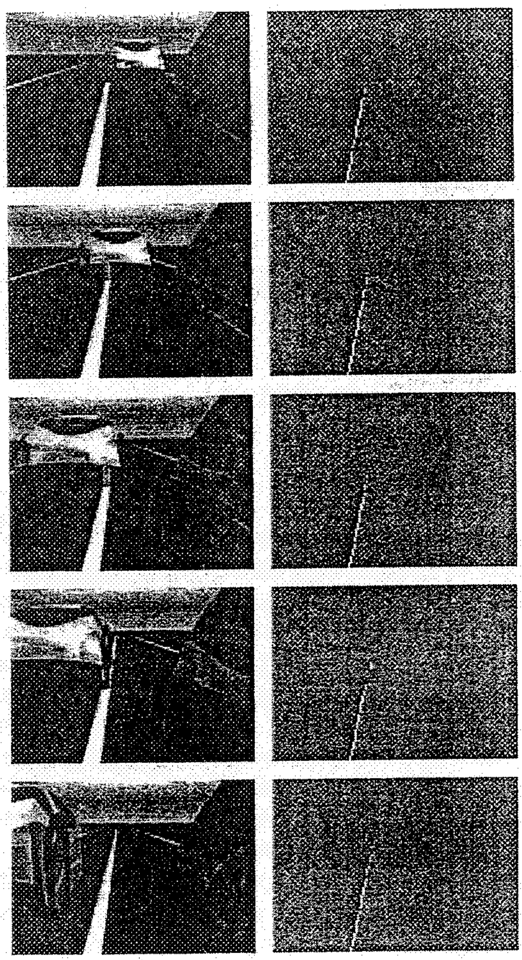

Figure 13: The scene of overtaking and the detected white line

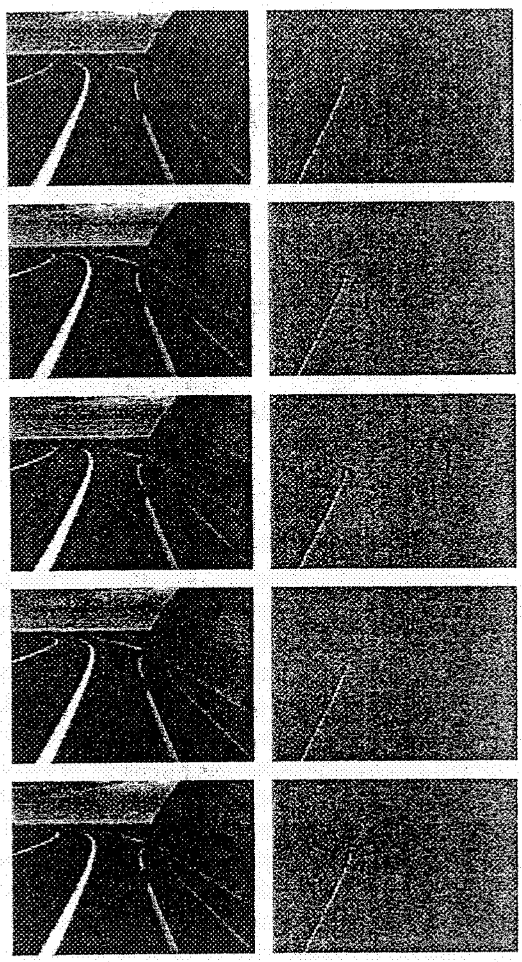

Figure 14: The scene of turning and the detected white line

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