MVA2005 IAPR Conference on Machine VIsion Applications, May 16-18, 2005 Tsukuba Science City, Japan
10-3

# A Reliable and Robust Lane Detection System based on the Parallel Use of Three Algorithms for Driving Safety Assistance

J. Douret & R. Labayrade
Livic (Inrets – Lcpc)
14 route de la Miniere 78000 Versailles, France
Jerome.douret@inrets.fr

Jean Laneurit & Roland Chapuis
Lasmea - UMR 6602 du CNRS
24 av. des landais 66177 Aubiere Cedex, France
Laneurit@lasmea.univ-bpclermont.fr

## Abstract

*Road traffic incidents analysis has shown that a third of them occurs without any conflict which indicates problems with road following. In this paper a driving safety assistance system is introduced, whose aim is to prevent the driver drifting off or running off the road. The road following system is based on a frontal on-board monocular camera. In order to get a high degree of reliability and robustness, an original combination of three different algorithms is performed. Low level results from the first two algorithms are used to compute a reliability indicator and to update a high level model through the third algorithm using Kalman filtering. Searching areas of the roadsides for the next image are also updated. Results obtained in the context of the ARCOS[1] French project show the reliability, the robustness and the precision of this original association of three different algorithms in various situations, including roads with high curvature.*

## 1 Introduction

More than 30% of road accidents are caused by road following issues. Two criteria can be enounced to qualify the driving consistency depending on the road configuration. The first one is the distance of the vehicle from its lane border and holds on straight lines. The second one is the geometric characteristics of the road related to the dynamic of the vehicle. It becomes preponderant in curves and supports to the need of an anticipated detection in front of the vehicle.

Based on those criteria, driving safety assistance consists in warning, suggesting or correcting the driver if he has not manifested the aim of a voluntary lane change or if his speed is not adapted with the road configuration. All these assistance modes rely on a system that is able to localize the vehicle with respect to the road and to model the shape of the road itself. This task is usually done through image processing using a frontal camera.

To be accepted by drivers, such a system must have a high degree of robustness and reliability. It must be able to deal with various meteorological conditions (day, night, sunny, rainy), various road profiles (straight lines, longitudinal or lateral curvatures), different lines configurations (continuous, dashed, way out) and also with occluded or degraded road markings.

Moreover the system must be able to know its operating state. This means that it has to automatically switch off when nothing is seen or when the detection is not enough confident. This is a point of great importance in any assistance system.

Vision systems aimed at detecting the road have been subjected to investigations for many years [5]. Many different solutions were proposed in literature:

- In [11] the road is assumed to be flat and straight. This model is the simplest one. But this approach is very restrictive and one can not use it on curved roads.
- Broggi and al. [3] proposed the so-called *Inverse Perspective Mapping* transform to remove the perspective effect. The lane markings are then quasi-vertical white lines and are extracted assuming a constant width. This method is efficient only in short distance and in a weak curvature road.
- Dean Pomerleau [9] uses a similar system and computes histograms to improve robustness.
- Tarel and al. [6] proposed a curve extractor from a set of line segments grouped in a decreasing order of their length. This method is robust to bad lighting conditions but is quite time consuming.
- Algorithmic redundancy is proposed in [8] through the use of two low level algorithms so to obtain a reliability indicator. However this method does not take into account a high level road model, which can lead to detection failures especially in the case of high curvature roads. Moreover the horizon line is supposed to be constant.
- In [4] the yaw, roll and pitch are estimated but the road width is still assumed constant. However in practice, the road width generally varies.
- In [1] an efficient model-driven approach taking the vehicle dynamics into account is proposed. However the feature extraction process is rough, the algorithm is recursive and can hence be computational exponential, and the system can hardly provide any reliability indicator about its operating state.

It seems to us that combining various systems could be of great interest. That is why we propose the parallel use of the model-driven approach proposed in [1] and the low level process introduced in [8], in order to take advantage of each system. The resulting system is aimed at managing any kind of roads and situations, and providing a reliability indicator about its operating state. Principles of the three algorithms will be reminded and the original way in which they are combined will be described. Eventually results will be presented and show that the new detector is efficient in any situation.

---

1 *Research Action for Secure Driving*

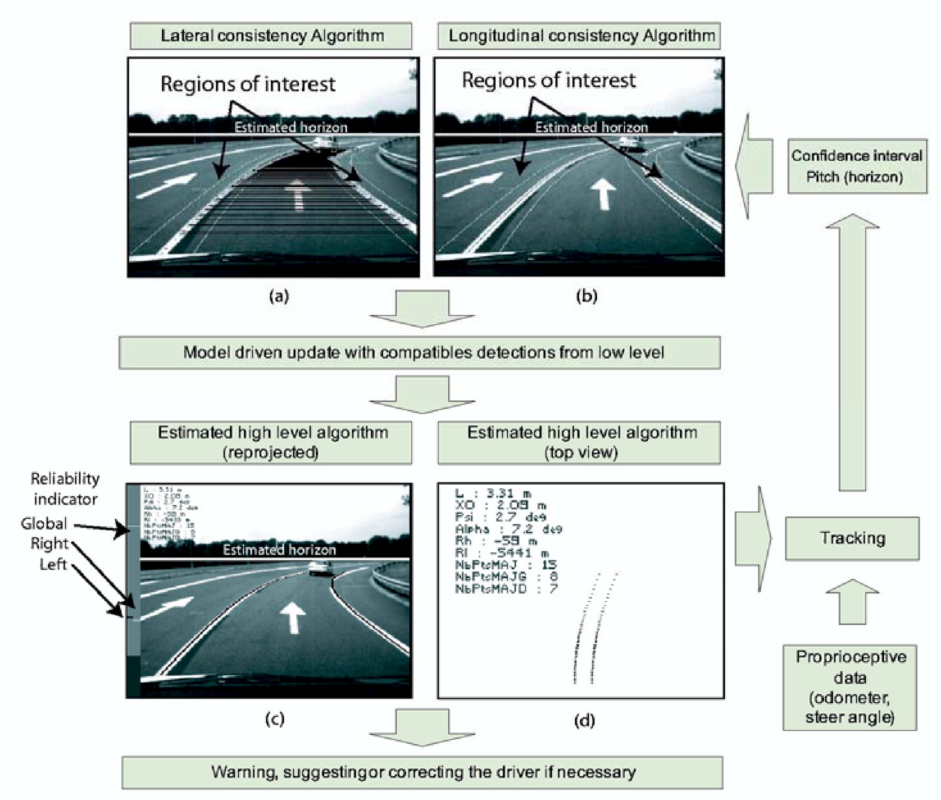


Figure 1. System overview

## 2 Algorithms Description

First an overview of low level algorithms is presented. More details can be found in [8]. Then their combination is described. Eventually the way in which coherence of data and vehicle localization is ensured [1] is explained. Focus is done on the link between low level and high level algorithms.

### 2.1 Low level detection

#### 2.1.1 Lateral consistent detection

The algorithm used for the lateral consistent detection consists in a simple low-level processing. It processes each scanning line independently. This algorithm can be divided into three main stages: (1) features extraction in the image that are likely to belong to a road marking; (2) matching of primitives between the left and right lane borders; and (3), tracking over time.

The feature extraction is aimed at obtaining the maximum number of features present on the lane-markings while largely reducing the number of outliers. With the frontal camera, the observed lane-marking width decreases linearly and reaches zero at the horizon line. Thus, the extractor computes intensity gradients of a value higher than a threshold $s_0$ and then searches for a pair of positive and negative gradients within a range $[s_1, s_2]$ that depends on the current line of analysis, because of the perspective projection on the camera. Then the center of the pair is selected as feature.

The matching process selects, for each line of analysis, the couple of primitives that is more likely to describe the left and right borders; the chief criterion is the horizontal distance of the left and right features, which must be as close as possible to the width of the lane.

The tracking step computes the new positions of the left and right borders, and can manage non-continuous markings. Figure 1 (a) shows the result of this algorithm.

#### 2.1.2 Longitudinal consistent detection

The second low-level algorithm is divided in two parts: a lane marking features extractor and a robust road shape estimation based on M-estimators.

The lane marking features extractor is very similar to the one used for the lateral consistent detector presented in the previous section.

In the robust road shape estimation, we consider that the extracted features are noisy measurements of an underlying curve explicitly described by:

$$u = \frac{a_{-1}}{v - v_h} + a_0 + a_1 v = X(v)^T A$$

where $A = (a_{-1}, a_0, a_1)^T$ is the parameters vector to be estimated, and $X(v) = (1/(v - v_h), 1, v)^T$ is the hyperbolic polynomial basis. The road shape estimation is based on the M-estimators theory. The use of the M-estimators leads to the well-known weighted least square algorithm that provides robust estimations [10]. Figure 1 (b) shows the result of this algorithm.

#### 2.1.3 Combining low level algorithms

Each low level algorithm has provided an output. For each line of analysis $i$, the evaluated positions of the left and right borders are available from both algorithms. If these positions, from each algorithm, are close to each other (horizontal distance less than a few pixels), the detection on the line $i$ is assumed to be reliable and the average position between the two algorithms is to be taken into account for the next process. Otherwise the line $i$ is rejected. The confidence value indicating the operating state of the system is given by the percentage of lines of analysis where the detection is assumed to be reliable for left and right borders and is summed up for the global reliability indicator (cf. fig. 1 (c)).

## 2.2 Data coherence, vehicle localization

This section describes the method allowing to improve coherence between the low level detection (image data, section 2.1) and vehicle 3D localization (section 2.3) and to predict regions of interest used by the low level detection (section 2.4). Coherence will be obtained by a statically learning [1] (training stage) and imposes to integrate image data and 3D parameters in a single one state vector $\underline{X}=(\underline{X}_d,\underline{X}_l)$, vector $\underline{X}$ and training stage are described in next paragraphs.

**3D localization vector $\underline{X}_l$ :** Road geometry and vehicle position are described by the state Vector $X_l=(L,X_0,\psi,\alpha,C_h,C_l)^t$ and its covariance matrix $\mathbf{C}_{X_l}$ representing errors on 3D model. $X_0$ is the lateral position of the vehicle on the roadway, $L$ the road width, $\psi$ the vehicle steer angle, $\alpha$ the camera inclination angle (pitch), $C_h$ the horizontal road curvature, $C_l$ the evolution of the horizontal road curvature.

**Image data $\underline{X}_d$ :** Image data are represented by a vector $\underline{X}_d=(u_{1l},\dots,u_{nl},u_{1r},\dots,u_{nr})$ and its covariance matrix $\mathbf{C}_{X_d}$. Where $(u_{1l},\dots,u_{nl})$ and $(u_{1r},\dots,u_{nr})$ represent the image abscissas of the left and right road sides for different image ordinates $v_i$ $(i\in[1,n])$ fixed once and for all. The matrix $\mathbf{C}_{X_d}$ defines the variations of coordinates $u_{il}$ and $u_{ir}$ (see figure 2).

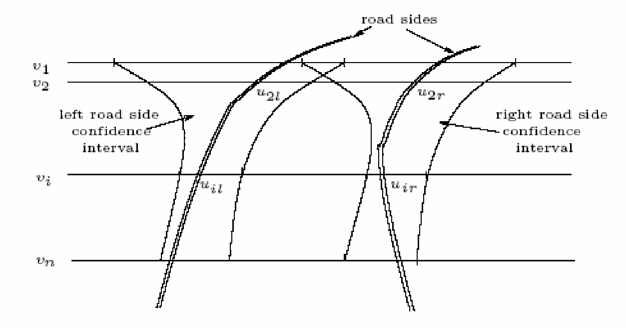


Figure 2. Image data

**Training stage:** This stage allows to compute the dependencies between the 3D parameters and image data while knowing the distribution probability of the 3D localization parameters defined by $N(\underline{X}_l(0),\mathbf{C}_{X_l}(0))$ (vector $\underline{X}_l(0)$ represents the mean value of 3D parameters and covariance matrix $\mathbf{C}_{X_l}(0)$ their possible variations). These dependencies can be described by the distribution probability $N(\underline{X}(0),\mathbf{C}_X(0))$ and will be used as a reference for 3D estimation and tracking stage (sections 2.3 and 2.4).

## 2.3 Parameters estimation

Once an estimation of the roadsides location for a given image $k$ is achieved (see 2.1.3), low level detection provides a vector $\hat{\underline{X}}_d(k|k)$ with its covariance matrix $\mathbf{C}_{\hat{X}_d}(k|k)$. $\hat{\underline{X}}_d(k|k)$ is chosen as the average points from low level algorithms that have been classified as reliable and $\mathbf{C}_{\hat{X}_d}(k|k)$ is made from the distance between reliable points. This way robustness of the inputs of the model driven algorithm are enforced and the global efficiency of the system is increased.

Then, in order to estimate all parameters for the given image, we update the vector model $\underline{X}(k|k)$ in the following way:

$$\begin{cases} \underline{X}(k|k)=\underline{X}(0)+\mathbf{K}_d\left[\hat{\underline{X}}_d(k|k)-\mathbf{H}_d\underline{X}(0)\right] \\ \mathbf{C}_X(k|k)=\mathbf{C}_X(0)-\mathbf{K}\mathbf{H}_d\mathbf{C}_X(0) \end{cases}$$

- $\mathbf{K}_d=\mathbf{C}_X(0)\mathbf{H}_d^T\left[\mathbf{H}_d\mathbf{C}_X(0)\mathbf{H}_d^T+\mathbf{C}_{\hat{X}_d}(k|k)\right]^{-1}$
- $\mathbf{H}_d$ is such as $\hat{\underline{X}}_d=\mathbf{H}_d\underline{X}+\underline{w}_d$ with $E\left[\underline{w}_d\underline{w}_d^T\right]=\mathbf{C}_{X_d}$

## 2.4 Tracking stage

Before new roadsides recognition, an *a priori* knowledge of the position of the image data is needed to drive the search for interest points. This stage can be computed in two steps.

**Prediction of the 3D localization:** Between two images, it is possible to know the behavior of the vehicle attitude (position $X_0$ and orientation $\psi$) on the road taking into account data provided by proprioceptive sensors embedded in the vehicle. So an estimation of the 3D localization at image $k+1$ can be computed by the following relation $\underline{X}_l(k+1|k)=f(\underline{X}_l(k|k),\Delta d,\delta)^T$, $\Delta d$ and $\delta$ are respectively odometer and steer angle data.

**Initialization of the low level detection:** In order to compute the new regions of interest for low level detection, the vector $\underline{X}_d(k+1|k)$ must be estimated. Then state vector $X(k|k)$ is updated taking into account $\underline{X}_l(k+1|k)$ and the covariance matrix $\mathbf{C}_{X_l}(k+1|k)$ :

$$\begin{cases} \underline{X}(k+1|k)=\underline{X}(0)+\mathbf{K}_l\left[\hat{\underline{X}}_l(k+1|k)-\mathbf{H}_l\underline{X}(0)\right] \\ \mathbf{C}_X(k+1|k)=\mathbf{C}_X(0)-\mathbf{K}\mathbf{H}_l\mathbf{C}_X(0) \end{cases}$$

- $\mathbf{K}_l=\mathbf{C}_X(0)\mathbf{H}_l^T\left[\mathbf{H}_l\mathbf{C}_X(0)\mathbf{H}_l^T+\mathbf{C}_{\hat{X}_l}(k+1|k)\right]^{-1}$
- $\mathbf{H}_l$ is such as $\hat{\underline{X}}_l=\mathbf{H}_l\underline{X}+\underline{w}_l$ with $E\left[\underline{w}_l\underline{w}_l^T\right]=\mathbf{C}_{X_l}$

Then, the new regions of interest for image $k+1$ are defined by $\underline{X}_d(k+1|k)$ and $\mathbf{C}_{X_d}(k+1|k)$, contained in the state vector $\underline{X}(k+1|k)$ and its covariance matrix $\mathbf{C}_X(k+1|k)$.
Moreover, the estimated pitch $\alpha$ is used to update in a dynamic way the horizon line for low level algorithms (cf. fig. 1). This significantly increases the feature extractions steps (lane markings width and road width).

# 3 Results

Results are part of the ARCOS project. The camera used had a focal distance f = 6 mm and was placed on-board near the rearview mirror. Images were 1/4 PAL,

$384 \times 288$ pixels. 150 horizontal scanning lines were chosen in the image corresponding to world lines between 3 m and 45 m from the vehicle by step of 30 cm and were used for low level detection. The model vector was composed of 18+6 parameters corresponding to 9 analysis zones for both left and right line. Initial values for the training stage were chosen in order to be able to deal with every type of road, including high curvature $C_h$ (cf. tab. 1).

Table 1. Initial values for the training stage.

| | $L$ (m) | $X_0$ (m) | $\psi$ (°) | $\alpha$ (°) | $C_h$ (m$^{-1}$) | $C_l$ (m$^{-1}$) |
|---|---|---|---|---|---|---|
| $\mu$ | 3.6 | 1.8 | 0.0 | 6.5 | 0.0 | 0.0 |
| $\sigma$ | 0.4 | 2.0 | 8.0 | 4.0 | 0.033 | 0.001 |

Tests have demonstrated the robustness of the algorithm. More than 300 km have been covered to date. Figure 3 represents results on different difficult situations the system has successfully dealt width. In figures 3(a) and 3(b) it manages large occlusions. The reader can notice the low right reliability value (right cursor in white on the left graduation). On figures 3(c) and 3(d) the system is switching off as soon as there is no more road markings. In 3(e) a large curve ($C_h \simeq 0.025 m^{-1}$) is followed by the system. Then in 3(f) it can be seen that the system handle well the so usual confusion with safety barrier. In 3(g) the system deals with a zebra road mark. In 3(h) the systems operates at night.

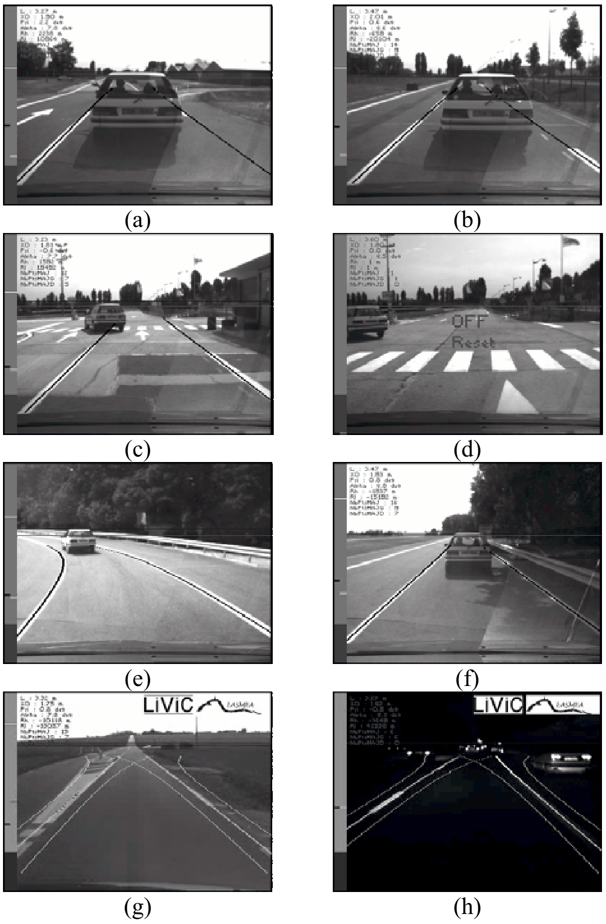


Figure 3. Example of results (see in text for detail)

Robustness of the system has been evaluated under different scenarios (day, night, sunny, rainy, highway, curved road, occlusions, imperfect road markings, etc.). Videos of various situations can be downloaded at: ftp://ftp.lcpc.fr/incoming/MVA/. The system has shown a really good behavior under all the tested situations. The system never returns erroneous results: it switch off when there is no correct result to return. The rest of the time the system operates well dealing with a large number of complex situations.

## 4 Conclusion

In this paper we introduced a lane detection system based on an on-board frontal camera for driving safety assistance. The originality relies on the parallel use of three different algorithms. The best of each one is developed whereas gaps are filled by the others. It results in a very robust system that can deal with almost all situations. A reliability indicator is provided to avoid reporting false detection which is crucial for the driver to be confident in the system and to be used safely for vehicle control. Results in real situations have demonstrated the robustness and efficiency of the system.

## References

[1] Aufrere R., Chapuis R., and Chausse F, ”A model-driven approach for real-time road recognition”, MVA, Vol. 13, No. 2, pp 95-107, Nov. 01.

[2] Broggi A., ”Robust Real-Time Lane and Road Detection in Critical Shadow Conditions”, SCV95, Active Vision I, pp 7A, 95.

[3] Broggi A., Bertozzi M., Conte G. and Fascioli A., ”ARGO prototype vehicle”, Intelligent Vehicle Technologies, pp. 445-493, 2001.

[4] Coulombeau P., and Laurgeau C., ”Vehicle Yaw, Pitch, Roll and 3D Road Shape Recovery by Vision”, IEEE IV’2002.

[5] Dickmanns E. D., and Zapp A., ”A curvature-based scheme for improving road vehicle guidance by computer vision”, SPIE Conference on Mobile Robots, Vol. 727, pp 161-168, Oct. 86.

[6] Guichard F., and Tarel J.-P., ”Curve Extraction Combining Perceptual Grouping and a Kalman Like Fitting”, IEEE ICCV’99, pp. 1003-1008, Sept. 20-25, 1999.

[7] Ieng, S.-S and Tarel, J.-P. and Charbonnier, P., ”Evaluation of Robust Fitting Based Detection”, ECCV2004, May 11-14.

[8] Labayrade R., Ieng S.S and Aubert D., ”A Reliable Road Lane Detector Approach Combining Two Vision-Based Algorithms”, IEEE ITSC 2004, pp. 149-154, Oct. 3-6, USA, 2004.

[9] Pomerleau D., ”RALPH: Rapidly Adapting Lateral Position Handler”, IEEE Symposium on Intelligent Vehicles, Sept., 1995, pp. 506 - 511.

[10] Tarel J.-P., Ieng S.-S., and Charbonnier P., ”Using Robust Estimation Algorithms for Tracking Explicit Curves”, ECCV’02, vol. 1, pp 492-507, Danmark, May 28-31 2002.

[11] Wang R., Xu Y., Libin, and Zhao Y., ”A Vision-Based Road Edge Detection Algorithm”, IV’2002.