On the Design of a Single Lane-Markings Detector Regardless the On-board Camera's Position [1]

Sio-Song Ieng
LIVIC
INRETS-LCPC
Versailles-Satory, France
email: ieng@inrets.fr

Jean-Philippe Tarel
IMEDIA
INRIA
Roquencourt, France
email: Jean-Philippe-Tarel@inria.fr

Raphael Labayrade
LIVIC
INRETS-LCPC
Versailles-Satory, France
email: labayrade@lcpc.fr

Abstract

In this article, we present an algorithm for lane marking features extraction and robust shape estimation of lane markings. The algorithm uses a new lane-marking features extractor followed by a robust fitting algorithm described in [13] to estimate the lane-markings shape as a single analytical curve. The lane-marking features extractor is based on the fact that lane-markings widths are in a small range of possible values, on a road. This implies a geometric constrain on the observed lane-markings widths from a camera on-board a vehicle. The lane-marking features extractor uses this property to select pairs of edge points corresponding with a high probability to a section of lane-marking. This features extractor is especially designed to be robust to lighting conditions as shown by few experiments. The extracted features are then grouped to estimate the parameters of the analytical curve model of these lane-markings. With the proposed approach, the obtained detector is robust to different kinds of noise and perturbations, allowing us to use it with a camera in many positions. Finally, to illustrate this property, we briefly describe two applications of the proposed detector: accurate vehicle location on the road and estimation of the time to line crossing.

1 Introduction

Metric and geometric information, about the road lane where the vehicle is, are the key information for improving road safety and/or for performing automatic vehicle guidance. Lane-markings detection and road modeling are thus really important for transportation applications and have been studied for a long time [8]. Depending on the camera orientation and position on the vehicle, one parameter or another is better estimated. For instance, when the camera is only looking at the lane-marking beside the vehicle, the accurately estimated information is the relative location of the vehicle with respect to the road center. When the camera is looking forward, the distance between the vehicle and the lane-markings is not accurate, but the curvature and more generally the path geometry in front of the vehicle can be estimated. This is why most of the vision systems for lane-markings detection are built with a camera looking forward. In the vision system that we have developed, several cameras can be used at different positions to give good estimates of path geometry as well as an accurate relative position of the vehicle.

2 Related Work

Many road models and lane-markings detection algorithms are proposed in the literature. Most of them extract lane-marking features and then group the extracted features to obtain the parameters of the road shape model. Among these methods, there are three kind of road models:

- The road is assumed to be flat and straight [6]. This model is the most simple one. But this approach is very restrictive and one can not use it on curved roads.
- The road is assumed flat and curved. This model allows an accurate road shape model by using clothoids or its approximation, for example.
- The 3D road model proposed in [2] needs a multi-sensor approach and temporal filtering to estimate the vertical curvature. A 3D road model is proposed in [4] with only one camera, but it assumes that road width, yaw, roll and pitch are constant or equal to zero. In [5] the yaw, roll and pitch are estimated but the road width is still assumed constant. However in practice, the road width generally varies.

Many algorithms use correlation techniques to extract features from the image that may be part of lane-

[1] This work is partly funded by Region de l'ile de France. The authors are grateful to LIVIC technical team for its help in the experiments.

0-7803-7848-2/03/$17.00 ©2003 IEEE

markings. To reduce the computational cost, this extraction is only performed on areas that are supposed to contain markings. In [3], this area is defined as a spatial probability distribution obtained from the previously detected markings. The well known Hough transform can also be efficiently used when a bird's eye view image is available [7]. Nevertheless, this approach can be applied only to straight roads. Another well known method is the peak and valley method [10]. Based on the gray level intensity variations, this last method detects maxima and minima of the gradient, and extracts the ones corresponding to the white markings on a dark road. Most of the time, these detectors are not robust enough in adverse lighting conditions. In [12] is introduced a new segment extractor based only on the geometric characteristics of the image for lane-markings extraction. This method is robust to bad lighting conditions but it is quite time consuming. We propose here a new lane-marking features extractor also based only on the geometry of lane-markings which is robust to lighting variations. This extractor is combined with a robust fitting algorithm described in [13] and extended here. The obtained detector provides robust estimates of lane-marking shapes as 2D parametric curves.

3 Marking Features Extractor

In our vision system, the camera can be mounted at different positions: frontal or/and lateral. The proposed lane-marking features extractor applies for all camera positions. Since lane-markings are simply seen as straight lines of constant width from a lateral camera, to describe the extractor, we focus on the frontal camera.

3.1 Lane-marking Model

The frontal camera is calibrated and at height h. Its optical axis and road make an angle θ. Fig. 1 shows the coordinate systems that are used.

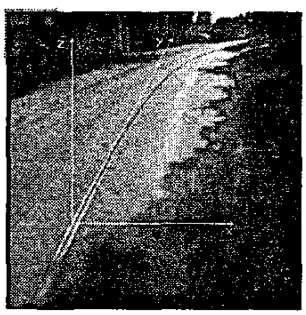

Figure 1: The road coordinate system is set on the centered and aligned with respect to the road. The image coordinate system is (u, v).

With the frontal camera, it is known that the observed lane-marking width decreases linearly and reaches zero at the horizon line. More formally, we have the observed marking width $l_m = \frac{\alpha_u \cos\theta}{\alpha_v h} l_v(v - v_h)$ where l_v is the road marking width, v_h is the coordinate of the horizon line, and α_u and α_v are respectively the inverse of a pixel width and length. Since lane-markings widths vary on real roads in a relatively small range of values $[C_1, C_2]$, we can use the previous linear model of the markings width to select, on an image line, features of a size compatible with the presence of a lane-marking. The feature we are using is just a set of positive and negative gradients within a distance $[S_1, S_2]$ which is compatible with possible lane-marking widths on the road. This is illustrated on Fig. 2 for a frontal image. Few outliers can be mistakenly selected as lane-marking feature but the number of outliers is relatively small due to the fact that the used geometric constrain is relatively strong.

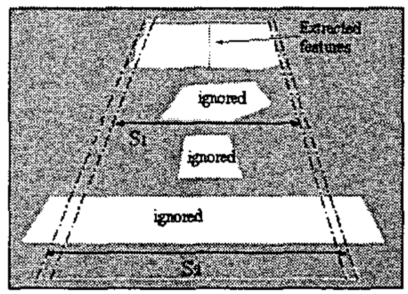

Figure 2: Lane-marking features selected on each line on geometric criteria only.

In practice, we do not use the two edge points of the extracted lane-marking feature. Its center turns out to be enough for a correct estimation of the road shape.

3.2 Extraction Algorithm

The proposed extractor first computes intensity gradients of a value higher than S_0 and then searches for a pair of positive and negative gradients within a range $[S_1, S_2]$. The goal is to obtain the maximum number of features really on the lane-markings and at the same time to reduce as much as possible the number of outliers, knowing that in any case the problem of outliers is tackled by the robust fitting algorithm of lane-markings. In order to not miss any feature, even in adverse lighting conditions, we have to set S_0 as small as possible and to analyze the whole image. It is always possible to limit the analysis in areas of interest thanks to a dynamic shape tracking, but this may induce problems if a new lane-marking appears. Fortunately, the proposed extractor is fast enough to be applied on whole image. For each line image, let u_{init} be the first position for which a gradient is greater than the threshold S_0, $u_{current}$ is the pixel position where image intensity is then strongly decreasing. A lane-marking feature is considered to be in the image line if $u_{current}$ -

u_{init} is within the range $[S_1, S_2]$ where $S_1 = C_1(v - v_h)$ and $S_2 = C_2(v - v_h)$. S_1 and S_2 are very important for removing many of the outliers, and thus C_1 and C_2 have to be chosen carefully. C_1 and C_2 can take into account different kind of errors such as small variations of marking width, errors on camera calibration. Here is the algorithm for every image line:

1. Calculate gradient $G(u_{init})$
2. If $G(u_{init}) > S_0$ then
   - $u_{current} = u_{init} + 1$;
   - $I = Intensity(u_{init}) + \frac{G(u_{init})}{2}$;
   - While $Intensity(u_{current}) > I$ and $u_{current} < sizeImageLine$
     - $u_{current} = u_{current} + 1$;
   - If $u_{current} \in [S_1, S_2]$ then
     - a marking is detected with center at $\frac{(u_{current}+u_{init})}{2}$;
     - $u_{init} = u_{current} + 1$, return to 1;
   - else, $u_{init} = u_{init} + 1$, return to 1;
3. else, $u_{init} = u_{init} + 1$, return to 1;

3.3 Features Extraction Results

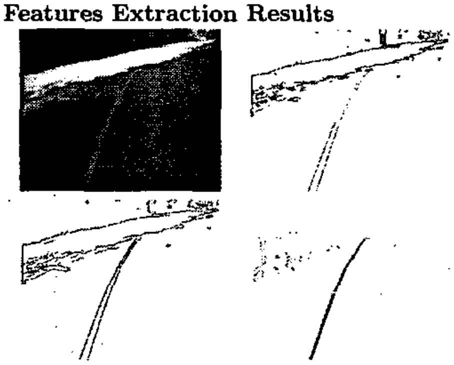

Figure 3: Top left: Original image of a road. Top right: result of Prewitt's filter. Bottom left: result of Canny's filter. Bottom right: result with our lane-marking features extractor. It is only with the proposed extractor that the high light area is removed.

With classical edge filters, every shadow or high light edges are obtained. With the proposed extractor, as shown in Fig. 3, we only have few outliers due to the high light area. Moreover the lane-marking is completely extracted.

4 Robust Road Shape Estimation

4.1 Road Model

2D flat road model neglects the vertical curvature of the road. For most of vehicle control applications, the shape of the road has to be estimated to a distance of 10 to $40m$. Therefore, a flat road model seems to be a not so bad approximation. Its main advantage is to allow estimation of the road shape from only one camera. The road shape is represented as a curve in a set of linear parametric models:

$$u = \sum_{i=0}^{d} f_i(v) a_i = X(v)^t A \qquad (1)$$

where (u, v) are the image coordinates of a point on the curve, $A = (a_i)_{0 \leq i \leq d}$ is the coefficient vector of the curve parameters and $X(u) = (f_i(u))_{0 \leq i \leq d}$ is a vector of basis functions of the image coordinate u. To reduce numerical problems a whitening of point data is performed by scaling the image in a $[-1, 1] \times [-1, 1]$ box for a lateral camera and in a $[0, 1] \times [-1, 1]$ box for a frontal camera.

This kind of linear family is particularly useful in setting up the shape estimation problem as a fitting problem and thus speeding up the detection. In practice, we model lane-markings on the road by polynomials $u = \sum_{i=0}^{d} a_i v^i$. The image of a polynomial on the road is an hyperbolic type polynomial with equation $u = b_0 v + b_1 + \sum_{i=2}^{d} \frac{b_i}{(v - v_h)^i}$, where b_i is linearly related to a_i [12]. The clothoid model is certainly the more realistic but also the more complex one. Fortunately, it can be approximated with a polynomial [8].

4.2 Feature Noise Model

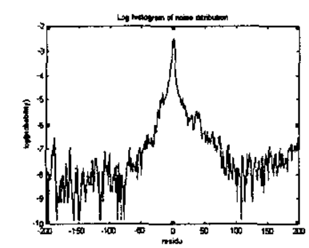

Figure 4: Logarithm of the distribution of errors in position of the extracted lane-marking features.

To our knowledge, only a few papers dealing with road shape estimation really discuss the robustness problem. Generally, the robustness problem is tackle by using a Kalman predicting filter combined with the threshold on the distance to the prediction. A Gaussian noise model is thus implicitly assumed. But, as already noticed in [13], the Gaussian model is not adapted for road images in many situations. This can be understood simply by looking at the logarithm histogram of the distribution of errors in position of the extracted feature. If the distribution is Gaussian, the obtained histogram should be a parabola. In practice, as shown in Fig. 4, we are far from a Gaussian distribution.

In [13], we have introduced a two-parameter family of noise models that fits the noise distributions observed in practice. This family is defined by the following probability distribution function (pdf):

$$pdf_{\alpha,\sigma}(b) \propto \exp(-\frac{1}{2}\phi_\alpha(\frac{b^2}{\sigma^2})) \qquad (2)$$

where $\phi_\alpha(t) = \frac{(1+t)^\alpha - 1}{\alpha}$. The first parameter α describes how much the pdf is heavy tailed. The second parameter σ is the scale.

4.3 Robust Parameter Estimation

We briefly present the fitting algorithm, since it is already described in details in [13], where proofs of convergence are explained. Then, we describe how this algorithm is used with different types of dynamic models and is improved with the use of a better covariance matrix.

We consider that the lane-marking centers, extracted as previously are noisy measurements of an underlying curve explicitly described by (1). Let us assume that the noise b belongs to family (2) on the u axis only. Thus we have $v = X(u)^t A + b$. The goal is to estimate the curve parameters A on the whole set n extracted feature centers (u_i, v_i), $i = 1, \cdots, m$. This problem is solved by an iterative reweighting algorithm, where at each step a linear problem is solved.

The fitting algorithm can be embeded in a tracking algorithm to take advantage of the temporal consistency between two consecutive images. The well known methods for tracking are certainly Condensation Algorithm [9] and Kalman filtering. The second one is very popular and used in many fields. Its main advantage is the linearity of the problem. But the noise on the curve parameters is assumed Gaussian. Condensation algorithm does not assume a Gaussian noise; it is estimated. From our experiments, the curve parameters noise seems not too far from Gaussian. Therefore, a Kalman like algorithm is better because it enforces more constrains and leads to a simpler algorithm. We thus introduced a robust kalman like filter that takes our specific noise family into account as explained in [13]. The main problem with using this robust Kalman filter is the need of correct estimates of the covariance matrix of the curve parameters after the robust fitting.

The covariance matrix of the curve parameters is easy to compute with Gaussian noise. For other kind of noise, we propose a new approximation C of the covariance matrix. In our experiments, this approximation performs better than many other approximations we have tested. The best approximation is given by:

$$C = \frac{\sum_{i=1}^{i=m} \lambda_i b_i^2}{\sum_{i=1}^{i=m} \lambda_i} O_1^{-1}$$

where $O_1 = \sum_{i=1}^{i=m} \lambda_i X_i X_i^t$ and λ_i are feature weights. The test was performed on a set of more than 100 real lane-markings images containing noisy points. Our approximate matrix was compared to the covariance matrix of the fits.

4.4 Dynamic Models

For lane-marking tracking, we have used three dynamic models that take into account the movement of the vehicle. The dynamic model is important when there is a fitting ambiguity between two lane-markings. With the use of a dynamic model, the detector is able to select the one closer to the predicted lane-marking.

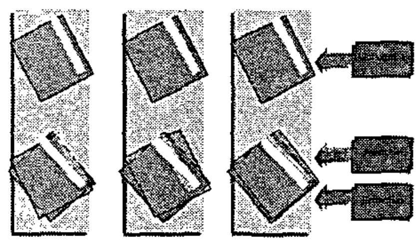

Figure 5: Left: motionless model for a lateral Camera. Center: translation model. Right: rotation and translation model.

Fig. 5 shows the possible behavior of the three dynamic models:

- The first model supposes that the vehicle does not move enough to notice any change in the lane marking state parameters.
- The second model supposes that the vehicle movement is only composed of a translation.
- The last model supposes the vehicle movement is composed of a rotation and a translation.

These models can be easily applied with lateral cameras as well as with frontal cameras. For lateral cameras, lane-markings are very close to the vehicle, so we can suppose that lane-markings are locally straight lines $x = a_0 + a_1 y$. In the frontal case, we must take the road curvature into account. For distances between $10m$ to $40m$, we assumed a road shape approximated by parabolas $x = a_0 + a_1 y + a_2 y^2$ on the road surface. We now only consider the second degree case since the straight line case is a particular case where $a_2 = 0$. We recall that, in the image coordinate system, the image of a parabola is described by $u = b_0 v + b_1 + \frac{b_2}{v - v_h}$ where b_i is a linear function of a_i depending of the camera calibration. Therefore, it is easy to derive the dynamic model in the image from the dynamic model on the road surface.

When a translation of the vehicle is assumed, we have to write the road shape estimated at time $t-1$ in the new road coordinate system at time t. This transformation is $x_t = x_{t-1}$ and $y_t = y_{t-1} + \delta d_{t-1}$, where δd_{t-1} is the followed distance. The curve $x = a_{0,t-1} + a_{1,t-1}y + a_{2,t-1}y^2$ becomes $x = a_{0,t} + a_{1,t}y + a_{2,t}y^2$, where $a_{0,t} = a_{0,t} + a_{1,t-1}\delta d_{t-1} + a_{2,t-1}\delta d_{t-1}^2$, $a_{1,t} = a_{1,t-1} + 2a_{2,t-1}\delta d_{t-1}$ and $a_{2,t} = a_{2,t-1}$.

When a rotation and a translation of the vehicle is assumed, the change of coordinate systems is given by: $x_t = x_{t-1}cos(\theta_{t-1}) - y_{t-1}sin(\theta_{t-1})$ and $y_t = x_{t-1}sin(\theta_{t-1}) + y_{t-1}cos(\theta_{t-1}) + \delta d_{t-1}$. Considering $a_{0,t-1}$, $a_{1,t-1}$ and δd_{t-1} of order 1, and θ_{t-1} and $a_{2,t-1}$ of order 2, we can neglect third or higher orders terms and the predicted parameters at time t are thus given by $a_{2,t} = a_{2,t-1}$, $a_{1,t} = a_{1,t-1} + \theta$ and $a_{0,t} = a_{0,t-1} + a_{1,t-1}\delta d_{t-1}$.

	motionless	translation	trans.-rotation
5 iter.	42%	40%	9%
10 iter.	14.9%	13.3%	6.3%

Table 1: Fitting error in percentage for different dynamic models. The model with rotation and translation leads to more accurate solutions with less iterations.

A comparison was made, between these three models on synthetic images. We fitted curves on lane-markings on 500 lateral views. Then we compare the results given by our algorithm with the true parameters after 5 iterations and 10 iterations, for different dynamic models. As shown in Tab. 1, the use of a dynamic model allows us speed up the robust fitting convergence.

5 Applications

The detector previously described is designed in such a way that it can be used with a camera mounted on many positions on the vehicle. We have tested it with frontal and lateral cameras. Each position has its advantages and its drawbacks in terms of what can be measured accurately. We now present two applications of the detection algorithm that use two kinds of camera positions.

5.1 Time to Line Crossing

The frontal camera provides important geometric information about the road shape (see Fig. 6). With an analytical curve model, we are able to estimate its curvature and prevent lane departures by estimating the Time to Line Crossing (TLC). Knowing the polynomial equation of the lane-markings, the position of its intersection with the vertical straight line in the center of the image provides information on the TLC. Fig. 7 shows this point P_i on two images. The retroprojected point on the road is $P_r = (x_r, y_r, 0)$. Assuming the

Figure 6: Left: Camera directed forward on the LIVIC vehicle prototype. Right: Image seen from the frontal camera.

vehicle has a speed of s, and that P_i is known, we can calculate distance d_{lc} between P_r and the vehicle. Thus, the time to line crossing is given by $TLC = \frac{d_{lc}}{s}$.

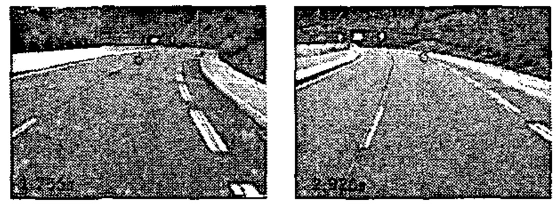

Figure 7: The circled point represents the lane departure point. From its v coordinate and the speed of the vehicle, we can calculate the Time to Lane Crossing.

This TLC estimation is very simple and is presented here to show the feasibility of such an application with our system. In [14], more complicated TLC computation are proposed.

5.2 Accurate Vehicle Localization

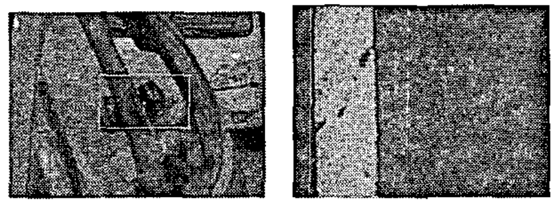

Figure 8: Left: Lateral camera on the LIVIC vehicle prototype. Right: Image seen from the lateral camera.

The accurate vehicle localization system merges several proprioceptive measurements, GPS measurements and lateral position from vision. The lateral camera provides images like the example shown in Fig. 8. With this position of the camera, the lane marking shape can be well approximated by a straight line. A map matching algorithm is then used to find the position of the vehicle [11]. This system was tested in real whether conditions on a test track of 3.5 kms. The result was analyzed and the estimated error of localization is around 5cm.

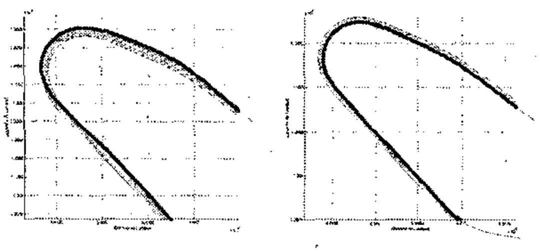

Figure 9: Left: Incorrect localization of the vehicle on the track without vision. Right: Correct localization with vision.

Fig. 9 shows how much the accuracy of the system is improved when the vision information is used. Without the vision the system can not determine correctly the lane of the vehicle.

6 Summary and Future Works

We have proposed a lane-marking features extractor based only on the lane-marking geometry. This extractor is fast, removes many outliers and at the same time extracts features with low contrast in the image. This extractor is combined with a linear fitting algorithm of curves that can be used inside a Kalman filter to track lane-markings. A new approximate covariance matrix is proposed allowing reliable robust Kalman like filtering. We also presented dynamic models that can be used in the robust Kalman like filter. The extractor combined with the fitting gives a lane-markings detector which is robust and relatively general. Particularly, this detector can be used with cameras mounted in many positions on the vehicle with few parameter modifications such as the degree of the curve model. This interesting property is illustrated by two applications that uses the proposed detector: estimation of the time to lane crossing and accurate vehicle localization. Further investigations will focus on how to take into account other road signs and/or road intersection lane-markings by improving first our features extractor.

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