Robust lane recognition embedded in a real–time driver assistance system

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Abstract—

We developed a fast and robust approach for automatic lane detection as part of a real–time driver assistance system. Two different algorithms to extract measurement points are used to detect not only marked but unmarked lane borders as well.

Different road types as well as various traffic situations and illumination changes require great care on robustness and reliability. Obstacle information computed by another module in this system helps to increase robustness.

The algorithm was extended to track two directly neighboured lanes. Additionally, the distribution of the measurement points is used to classify the marking line types.

The system has been integrated into two experimental vehicles and tested with a large data set. It performed very well under different traffic situations and weather conditions.

I. Introduction

An important component of a driver assistance system is the evaluation of image sequences recorded with cameras mounted in a moving vehicle. These image sequences provide information about the vehicle's environment which has to be analysed in order to support the driver in real traffic situations. A systematic overview on the development of image sequence analysis systems for road vehicles is given in [1].

One important function of a driver assistance system is the robust detection and tracking of road boundaries. This information is required to control a vehicle's lateral position on the road, to detect obstacles in the own lane or to warn a driver when leaving the road.

While some authors [2], [3] model the lane borders in the two-dimensional image plane, Dickmanns and Graefe [4] showed the benefits of applying a dynamic spatio-temporal 4D model to solve this task. A Kalman filter uses image features that are extracted within some image regions of interest to recursively estimate relevant system state variables [5]. Even with moderate computing power road tracking has been sucessfully accomplished on some road types with vehicle speeds up to 130 km/h [6], [7], [8].

These dynamic models use explicit knowledge about the expected scene, the imaging system and the dynamic behavior of the vehicle. Thus image processing can be restricted to small predictable regions within the whole image and enables real–time processing.

Luong et al. [9] presented an approach which evaluates pairs of stereo images to avoid the selection of image features for state estimation that come from an elevated object.

In contrast to approaches that use contour based information, texture based image processing methods have been investigated [10] but are currently not implemented in the vehicle due to real–time requirements. Alternatives are region-based approaches for road detection such as a watershed transformation [11] or classification of color regions [12].

In the ROMA-System [13] it has been shown that — based on aggregation of simple image features to road markings and calculating the parameter values of lane markings — sufficiently good intersection hypotheses can be generated from gray value images. This is an important task in more complex situations such as urban traffic situations [14].

In this contribution we use a lane state model which is based on the work of Dickmanns and Mysliwetz [5]. World parameters of clothoide shaped lane borders with horizontal and vertical curvature are estimated with a Kalman filter. To investigate whether additional vehicle sensors can be avoided, the measurement of the vehicle motion is restricted to speed information only. Therefore, a restricted dynamic model was set up.

Measurement points are extracted using gradient based methods. Different measurement point extraction algorithms are used to handle different road border types.

Especially for system integration purposes, the lane recognition module checks whether the state estimation result is reliable or not. If lane borders are partially hidden — e.g. by other cars — we use the results of an obstacle detection module to increase the robustness of the lane tracking module. The obstacle detection procedure is based on the analysis of motion compensated difference images similar to the approach of Carlsson and Eklundh [15].

To extract additional information from each image the algorithm was extended to track two neighbouring lanes simultaneously with the current (main) lane by a similar estimation process. Reliability tests had to be added to avoid incorrect detections.

A classification of marked lane border types based on the already detected measurement points of the lane tracking algorithm leads to a higher level representation of the road.

II. Model for Lane and Vehicle Movement

A. The state vector

The lane state used in this approach consists of parameters which describe the shape of the current lane and the position of the vehicle on the road with respect to the lane. The shape of the lane is assumed to be a clothoide, which is approximated by a third order polynomial in the world coordinate system (z–axis to the front, y–axis to the right, and x–axis upwards).

The camera is mounted in the vehicle with known height h. Known offsets in yaw, pitch and roll angle between the optical axis and the longitudinal axis of the vehicle are used for robustness against inaccuracy of the camera mounting.

The lane state vector consists of seven elements:

- φ_1: yaw angle between the longitudinal axis of the vehicle and the tangent of the lane.
- φ_2: pitch angle between camera and road.
- y_0: lateral offset of the vehicle to the lane center.
- b: lane width.
- c_{h0}: horizontal curvature.
- c_{h1}: alteration rate of the horizontal curvature.
- c_{v0}: vertical curvature.

A pitch angle less than zero corresponds to a camera pointing downwards, a positive yaw angle to a lane tangent bent to the right. Horizontal curvature parameters greater than zero correspond to a lane curved to the right, vertical curvature parameters greater than zero to a lane curved upwards.

It is assumed that the horizontal and vertical curvatures are independent from each other. This approximation holds for small curvature values. On mountain roads with great horizontal and vertical curvatures, this assumption is invalid.

B. Model Equations and Estimation

The image corresponding to a lane given by some state vector can be computed by perspective projection. The intrinsic camera parameters f_x and f_y (scaling factor, composed of focal length and pixel pitch) and c_x and c_y (principal point) are assumed to be known by a calibration procedure.

In the following, we assume that the considered angles are small. With a small yaw angle, the look ahead distance l of a lane border point, which is measured along the lane, is approximatly the same as the z–coordinate of the point. The image coordinates of a lane border point is then computed by the equations depending on l:

$$x_b = \frac{f_x}{l}\Big(y_l - y_0 + \varphi_1 l\Big) + c_x \qquad (1)$$

$$y_b = \frac{f_y}{l}\left(h + \varphi_2 l - \frac{c_{v0}}{2} l^2\right) + c_y \qquad (2)$$

The y–coordinate of the lane border point y_l in the world coordinate system is given by

$$y_l = \pm\frac{b}{2} + \frac{1}{2}c_{h0}l^2 + \frac{1}{6}c_{h1}l^3, \qquad (3)$$

where plus and minus signs correspond to the right and left lane borders respectively.

Given the measurement vector $\boldsymbol{x}$ of horizontal image coordinates, the optimal state $\hat{\boldsymbol{s}}$ can be estimated by minimization of the quadratic error:

$$\hat{\boldsymbol{s}} = \underset{\boldsymbol{s}}{\operatorname{argmin}} \Big[(\boldsymbol{x} - \boldsymbol{g}(\boldsymbol{s}))^T \boldsymbol{R}^{-1} (\boldsymbol{x} - \boldsymbol{g}(\boldsymbol{s})) + (\boldsymbol{s} - \boldsymbol{s}_0)^T \boldsymbol{P}^{-1} (\boldsymbol{s} - \boldsymbol{s}_0) \Big] . \quad (4)$$

The covariance matrices $\boldsymbol{R}$ and $\boldsymbol{P}$ of the measurement noise and the initial state $\boldsymbol{s}_0$, respectively, are assumed to be diagonal with known elements.

Since the measurement function

$$\boldsymbol{g}(\boldsymbol{s}) = \left(\frac{f_x}{l} \Big(y_l - y_0 + \varphi_1 l \Big) + c_x \right)_l \quad (5)$$

is nonlinear, the estimation is done by linearization and iteration. The different values for l in the vector–valued function $\boldsymbol{g}$ are evaluated by solving Equation (2) wrt. l, using the image coordinates y_b of the extracted measurement points.

The lane state is predicted to the next image with time difference Δt by

$$y_0 \leftarrow y_0 - v \, \varphi_1 \, \Delta t \quad (6)$$

$$c_{h0} \leftarrow c_{h0} + c_{h1} \, \Delta t \quad (7)$$

with known speed v of the vehicle.

Since measurement of the vehicle's motion is restricted to speed information, a more complex motion model was not set up. Therefore, we decided not to use the covariance prediction of the Kalman filter. Instead, the covariance matrix of the prediction is set to a constant diagonal matrix.

III. Measurement

A. Extraction of border point candidates

In the minimization Equation (4), $\boldsymbol{x}$ is a vector of horizontal coordinates of measurement points. In order to find them, horizontal scan lines are set in the image (Figure 1, left). The image row of a scan line corresponds to the distance in world coordinates on the road (Equation (2)). The position of a scan line in the image is defined by the projection of the predicted lane state into the image at this distance. In the initialization phase when no prediction is available, the given initial state $\boldsymbol{s}_0$ is used. The density of the scan lines in the image varies with the corresponding distances of the lane border points. Scan lines are set up to a maximum look ahead distance. Different extraction methods are used for measurement points on marked and unmarked lane borders (Figure 1).

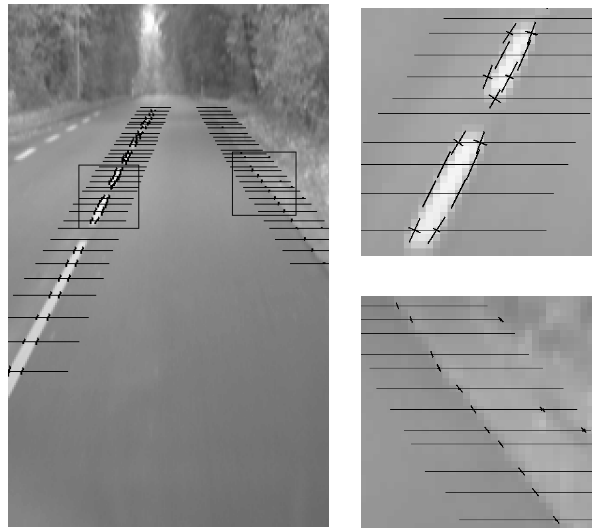

Fig. 1. Example of a marked and an unmarked lane border. The left image shows the scan lines set according to the predicted lane state and the extracted measurement points. Measurement points are marked as crosses, which display the eigenvectors and eigenvalues of the moment matrix. The crosses are rotated by 90° to demonstrate the matching of a measurement point with the contour in the image.

On each scan line, edge pixels are searched which are given by local maxima of gradient magnitude in gradient direction. At these edge pixels the moment matrix

$$\boldsymbol{M} = \begin{pmatrix} \mu_{2,0} & \mu_{1,1} \\ \mu_{1,1} & \mu_{0,2} \end{pmatrix} \quad (8)$$

is computed with the moments

$$\mu_{k,l} = \frac{1}{N^2} \sum_{i=-n}^{n} \sum_{j=-n}^{n} g_x^k(x_b + i, y_b + j) \, g_y^l(x_b + i, y_b + j) \quad \text{with} \quad k, l = 0, 1, 2. \quad (9)$$

$N = 2n + 1$ denotes a mask width. The functions g_x and g_y applied on the image point (x_b, y_b) return the x– and y–component of the gradient at that point, respectively.

The eigenvalues and the eigenvectors of the moment matrix are used to extract measurement point candidates. If both eigenvalues are small, the corresponding image region is homogenous.

In inhomogenous regions, both eigenvectors have eigenvalues of a significant magnitude. On edge structures one eigenvalue is significantly greater than the other. The eigenvector corresponding to the larger eigenvalue points into the direction of the steepest gray value ascent, the other one is orthogonal to this direction.

The quality of an edge pixel is computed by the ratio of the eigenvalues and the angle between the greater eigenvector and the tangent on the lane border given by the lane state. A marked lane border causes a pair of edge pixels which have antiparallel gradient directions. From each pair the inner point is taken as a measurement point candidate.

If not enough pairs can be found for the grouping algorithm described in the next section, the lane is assumed to be unmarked. In this case, single edge pixels are used as measurement point candidates.

B. Selection of border points

In general, more than one candidate for a measurement point can exist on one scan line. In the initialization phase, a robust straight line is estimated using only the innermost candidate points. If a line exists which approximates a minimum number of candidates, these candidates are used as measurement points to estimate the clothoide parameters. This leads to a robust initialization which can handle outliers. During the tracking phase, the candidate next to the predicted state is used as a measurement point on each scan line.

IV. Advanced Robustness

A. Validating the Estimated Lane

An important issue in lane tracking is robustness of the estimated lane state. To achieve a higher robustness, the system should be able to check the estimation's plausibility. Three different tests were implemented for this task, which are

- goodness of fit,
- tolerance interval check,
- gradient comparison.

To test the goodness of fit, the average distance of the measurement points to the corresponding estimated lane border projected onto the image is computed. If the average distance exceeds a certain threshold, the estimation is rejected.

Tolerance intervals for each parameter are given, which describe the admissable range of the lane parameters. A large lateral offset indicates a lane change of the vehicle. In this case, the lane state is set to the new lane. If one of the other parameter lies outside of its interval, the estimation is rejected.

Since only the positions of detected measurement points are used to estimate the lane parameters, the gradient directions at these points are compared with the image tangents on the estimated lane borders. The estimation is rejected, if the lane borders do not fit sufficiently to the gradients of the measurement points.

If only one of the above tests rejects the estimation, the tracking of the lane is canceled, and the system will start a new initialization.

B. Using Obstacle Detection

The lane tracking algorithm proposed in this paper was developed as a part of a driver assistance system which includes a motion based obstacle detection module. The lane tracking algorithm benefits from the results of this module.

The lane tracking system cannot decide whether a measurement point is a point on the lane border or a point on an obstacle, e.g. a car in front of the own vehicle. Such wrong measurement points on obstacles can produce estimation errors, as shown in Figure 2. Additional information is necessary to avoid these errors. Using the obstacle information the vertical delimiters in the image of the car in front can be computed. Scan lines can now be cut on the delimiters. Therefore, wrong measurement points from obstacles will be avoided.

V. Estimation of Additional Lanes

In order to extract more information from each image, the two directly neighboured lanes of the current (main) lane are estimated as well. To do this, the same model and the same measuring method are used as for the main lane.

Some parameters of the neighbour lanes are assumed to be identical with the main lane, as the yaw angle and the curvature parameters. These parameters are not estimated for the neighbour lanes. The pitch angle is used to check the plausibility of the neighbour lanes. If the pitch angle difference between a neighbour lane and the main lane exceeds a threshold, the neighbour lane esti-

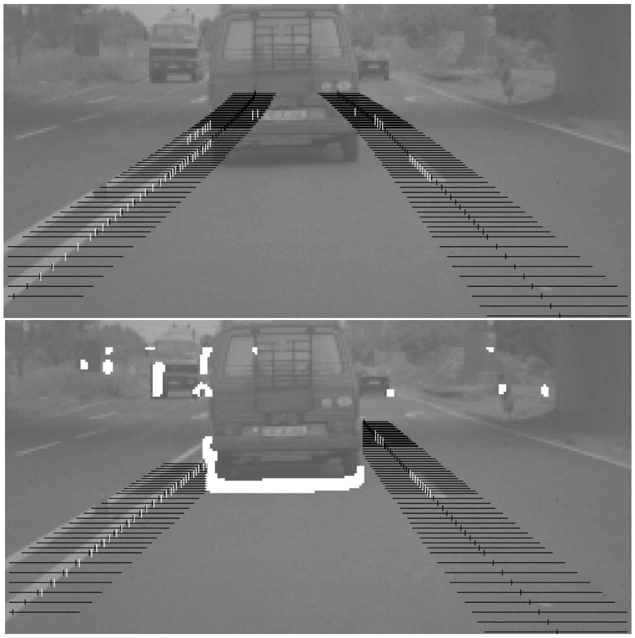

Fig. 2. Using obstacle information to avoid wrong measurement points. The top image shows a couple of wrong measurement points on the car in front as well as on the parallel marking line, since the correct points are hidden by the car. Due to these points, a wrong horizontal curvature to the left is estimated. The bottom image shows the obstacle mask and its use to cut the search lines along the obstacle borders.

mation is rejected.

Erroneous detections can happen on structures that look like lane borders, e.g. at crash barriers. Therefore, two additional tests are applied. The first one checks the homogeneity of a neighbour lane. The second one tests if there are any obstacles inside the image area of the neighbour lane. If one of the tests is not successful, the neighbour lane is rejected and a new initialization of the neighbour lane starts.

VI. Classification of Marking Lines

Marked and unmarked lane borders are distinguished during the detection of measurement points. A marked lane border can appear differently, e.g., as solid or as dashed marking line.

An algorithm was developed which distinguishes between solid and dashed marking lines by analysing gaps between the measurement points. The measurement points are sorted with ascending corresponding distance in world coordinates.

When a solid marking line is tracked, there will be measurement points on almost every scan line.

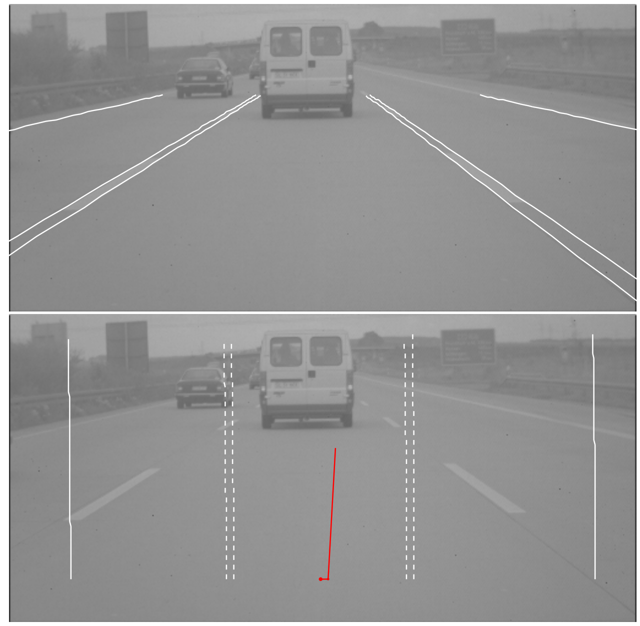

Fig. 3. Classified lane borders for current and neighbour lanes. The white lines show the lanes in a bird eye view. The black lines denote the vehicle's current position in the lane and its yaw angle. The width and the length of the lanes are not proportional.

On dashed marking lines, some scan lines will have no measurement point. The gap size between two successive measurement points is computed in world coordinates by the difference of the look ahead distances corresponding to the measurement points.

If the maximal gap size in the world for one lane border exceeds a threshold, the border is classified as a dashed marking line, otherwise it is classified as a solid line.

VII. Experimental Setup and Results

The situation–oriented multilane recognition module has been integrated into a system together with the obstacle detection module. The system works on gray level images taken by a single camera fixed at the front window of the vehicle. In order to develop a low cost real–time system, the algorithm has been implemented on a 333 MHz standard PC with a Pentium II processor without using any special hardware components. The system has been integrated into two experimental vehicles. Experiments have been performed online in the cars as well as with more than 150 000 images taken in a variety of scenes with different environmental conditions.

The system runs with an overall cycle rate of 14 Hz, including the time consuming obstacle detection module. The lane tracking module needs only 15 ms per cycle to estimate the current and neighbour lanes.

VIII. Conclusion

We proposed a robust real–time lane tracking system which can handle unmarked lane borders as well as marked lane borders. Robustness is achieved by a selection scheme of measurement points and various reliability tests of the estimated lane. We showed that the robustness of lane tracking can be increased by the use of an obstacle detection module.

The proposed algorithm was extended to track the directly neighboured lanes as well. A classification algorithm for lane types was given.

The result was integrated with an obstacle detection method to a robust and cheap overall system which is suitable for all–day use.

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