Map Guided Lane Detection

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This article addresses enhancements and optimizations of a lane detection system through sensor fusion methodology. Challenging tasks have to be considered, e.g. illumination or pattern mismatches. Therefore the digital map is used as a guide to a precise and fast lane model estimation process, allowing the introduction of constraints. Scan lines are projected into the image domain to get the search paths. The (re-)initialization can be improved e.g. in curve scenarios by adapting dynamically the search region to the expected road geometry. The developed system is compared to the original system using several scenarios. The results show a significant improvement of the overall performance, showing the advantages of integrating multiple sensors like a High Dynamic Range camera and digital map data into the next generation of lane detection systems.

Keywords: map guidance, lane detection, lane departure warning, direction overlay, lane model

1. Introduction

Accidents caused by lane departure or collision with lateral traffic result in18.312 injured and 134 dead people in Germany in 2006 [1]. Most of these accidents are caused by inattention of the drivers, and could be avoided by automatic warning systems. In our approach, we concentrate on unintended lane departures. Challenges rise from uncountable environment variables, e.g. illumination conditions, road types or mismatching patterns, that influences the determination of the relative position between the car and the road. In this context, making the best use of all available sensor data is fundamental.

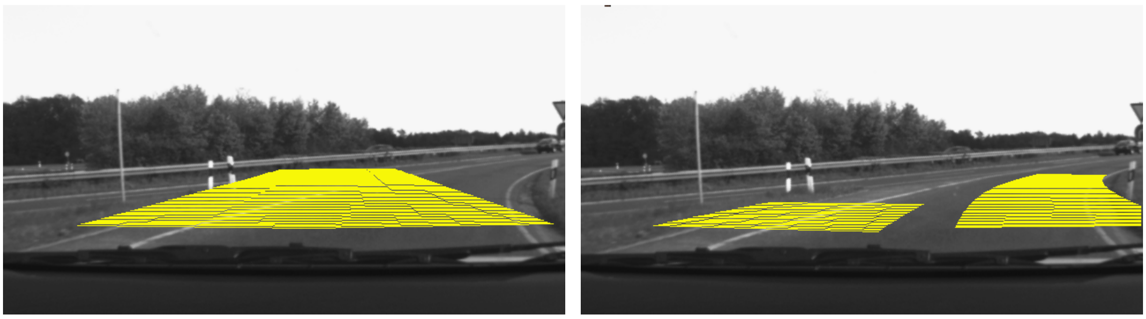
2. State-of-the-art

Regarding the most representative works on the application of maps and positioning devices to support lane detection algorithms, Cramer presented a method that fuses image and map data and evaluates various other sensor fusion approaches [2]. The reconstruction of the road geometry out of digital map data is content of the work from Tsogas [5] and Weigel [6]. They concentrate on the enhancement of the recognition task especially in far distances. In difference to the previously mentioned publications, we consider map and positioning device data as a guide to the lane model estimation process. This leads to a higher precision and accuracy compared to single camera approaches.

3. Methods

Our system is composed of a positioning device, a computational unit, e.g. a notebook or a PDA, and a High Dynamic Range (HDR) camera facing towards the driving lane. The base methodology is described in [3] and [4]. The complete system is designed to be easily ported to several embedded platforms. Minimal working performance can already be achieved with ARM11 processors. Video acceleration co-processors designed for solving pre-processing tasks in hardware, e. g. edge detection, are well suited to increase significantly the overall performance. An acceleration module, fitting low cost FPGAs as the Altera EP2C8, presents already real time performance in combination with a 133MHz processor with floating point unit (FPU) (tested with a NIOSII soft-core processor). Additionally the fusion of the digital map leads to further improvements in computational speed, as will be described in the sequence.

The introduction of the map information into the lane detection system starts at the definition of the search region, the area where the lane is expected to be in the image space. 3D lines orthogonal to the lane direction, along a certain range in front of the vehicle, are projected into this space to define the search paths. In the single camera system, the lane geometry is fixed, what in many cases, especially in curves, avoids the (re-)initialization of the algorithm. By adapting dynamically this region to the expected road geometry, more features can be correctly selected, and hence a model can be estimated. Fig. 1 shows this procedure.



a) b)

Fig. 1: Projection of scan lines: a) without and b) with adapted initialization parameters.

Edges are then searched along the previously described scan lines. In the sequence, a process selects the best marker candidates according to specific physical constraints. At this point a generalized Hough transform is applied to find a third degree polynomial, approximating a clothoid curve.
The model is given by:

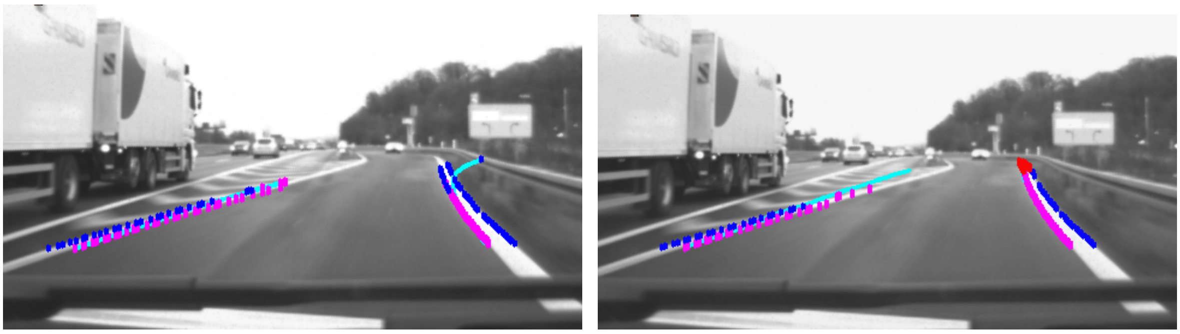
$$y(x) = \frac{1}{2} c_0 x^2 + \frac{1}{6} c_1 x^3 \pm \frac{b}{2}$$

where y is the lateral offset, c_0 is the curvature, c_1 is the curvature change, b is the lane width and x the distance from the vehicle along the lane. The map geometry constrains the search region. Due to the high computational effort, the Hough space **h** is reduced to the four main parameters, defined by:

$$\mathbf{h} = \begin{bmatrix} \varphi_3 & y & b & c_0 \end{bmatrix}^T$$

where φ_3 denotes the yaw rate, necessary to compute x. By adjusting dynamically the search ranges through the local road geometry, we do not just enable the system to start in curve situations, but we also increase the precision of the algorithm, while maintaining the same computational effort.

Once a reasonable model is found an Extended Kalman Filter is applied to track it over time. The search regions are narrowed, following just the predicted model. If a bad estimation occurs, the search space in the subsequent frame will be incorrect, leading to worst models until quality checks force the system to re-initialize. In such situation it is interesting to fuse the predicted model to the map geometry. One approach would be to derive an intermediate model out of the two, like in [5]. In our approach the map serves as a guide for the lane detection. The map geometry is applied to define an extended search region. It is first aligned to the lane and projected into the image space, defining a guidance curve. Finally, the measurements are resampled in a certain region along this curve and the new model is estimated. If the map is wrong, features will not be selected in the new region, forcing the system to re-initialize. However, if the map geometry is correct, the re-sampling will provide a better feature set, and therefore a better model, stabilizing the detection. Fig. 2 shows a ramp scene before and after the re-sampling process. The blue marked points are measurements fitting 3D physical conditions of the lane marker, e.g. width and length. The estimated model is represented by the cyan curve and is fitted through selected points (marked in pink), as a result of the filtering process. At the right side, the red points indicate additional features selected from the extended search region. As a result of this approach, during the tracking operation, the lane is determined based only on image cues, assuring independence of the estimated model with respect to the map geometry.



a) b)

Fig. 2: Re-sampling process: a) before, b) after re-sampling.

4. Results

Test sequences of several scenarios with approximately 3500 images were manually annotated to serve as ground truth. The error between the estimated and the ideal system is calculated in the image space in order to avoid introducing errors of calibration parameters into the ground truth data. The absolute error is given by the Euclidean metric of lane points at the same distance from the car.

Table 1 shows the comparison for the four most common scenarios during a highway drive. Beside the average error, we compute the percentage of frames in which the system is kept in tracking operation, as a recognition rate metric.

Scenarios	**Original System**		**Map Guided System**	
	Tracking Time [%]	Avg. Error [pixels]	Tracking Time [%]	Avg. Error [pixels]
Entrance/Exit	76.7	16.2	93.8	4.2
Straight Road	93.1	2.7	96.6	1.8
Curve	57.9	9.5	78.9	4.1
Lane Change	82.5	3.2	92.5	2.4

Table 1: Evaluation of different scenarios between the original and the map guided system.

For the complete test data base, the system is kept 16.2% longer in the tracking mode than the original algorithm. The average error has fallen to 3.6 pixels, representing 13.8% less than the single camera system. In the final version of this paper, a more precise analysis of the improvements will be presented.

The images sequence in Fig. 3 demonstrates three frames from a ramp scene. In this scene the car is driving a curve with changing lane width. The comparison between the estimated lane model of the original system (left) is shown in contrast to the enhanced (right). One can easily see the strong bending of the model caused by poor feature selection in this sequence on the left hand side, while the enhanced system stays stable and the estimated model is much more reliable.

Fig. 3: Feature selection without (left) and with map constraints (right).

Fig. 4 shows the visual realization of the results: the green arrow indicates the driver which lane he should select. The turquoise lines highlight the actual detected lane. It can be seen that the lane is detected correctly although there are some noisy factors like the rear light of a car.

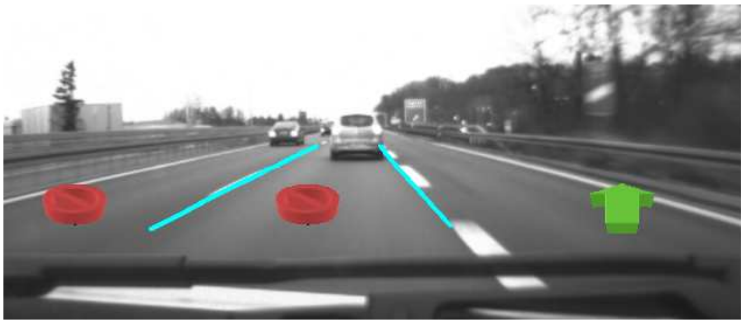


Fig. 4: Lane guidance demonstrator.

5. Discussion

In this work we have shown how maps can be introduced as guides to the lane detection process. Through the dynamic adaptation of the search space and by a better guidance of the initialization process, the system is now able to (re-)start in non-straight road situations. These adaptations lead to a better trade-off between precision and computational effort during the Hough transform phase. During the tracking operation, the introduction of the re-sampling approach avoids undesired bending of the lane model in situations where the feature quality at the far end is low. The new method contributes, first, to a more robust system, second, to a better precision of the estimation process and finally, by avoiding re-initialization phases, it also contributes to reduce the overall computational effort. Keeping the model estimation independent of the map geometry is therefore an interesting step towards an automatic mapping system.

Literature

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