

Stable Road Lane Model Based on Clothoids

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Abstract

In the following, the main concepts of a road lane model are presented that keeps track of an arbitrary number of lane borders. Information from an existing lane detection device, a gyrosensor, and map data are merged and filtered to create a road model with a desired number of road lines. The model is based on clothoids and continuously provides positions, angles, and curvatures of the border lines of the vehicle's own lane as well as of several neighboring lanes. Particularly on urban roads, in situations with upcoming turning lanes, or when the lane detection system fails to detect road lines, the model can still provide plausible information. This information significantly simplifies the situation analysis in further algorithms that rely on a lane detection system and require detailed information on current road lanes.

1 Introduction

Various advanced driver assistance systems are based on vision-based lane detection systems to determine characteristics of the current road and its lanes. Examples are lane departure warning or the lane keeping assistant that use the lane detection to support the driver to keep the lane. If the driver is distracted or careless, the system warns the driver by vibration in the steering wheel or by directing him back to the middle of his lane.

Difficulties arise when the lane detection system fails to recognize road lines or interprets objects as road lines that are not actually part of the current road. Especially in urban regions systems reach their limits. Vision-based approaches like in [1] use edge-oriented methods for a robust detection of road lines and approximate the course of the lanes by clothoids. These methods still fail if line markings are completely missing or covered by other vehicles. Subsequent systems that are based on lane detection have to deal with these inaccuracies and react properly.

Current driver assistance systems that rely on a lane detection method are mainly focused on highway situations. If the system needs only information on the own lane or if the vehicle drives on a highway with clear road markings, approaches as described in [2] can be used. It presents a multi sensor approach that fuses image measurements and map data to improve the tracking of road borders in highway scenarios. Another method as shown in [3] uses six cues and a particle filter to achieve robust lane tracking. This system is robust against dramatic lane changes and discontinuous changes in road characteristics. By using the Distillation Algorithm to track the vehicles pose relative to the road and their width, the system seems to be stable in situations that are critical for vision-based lane trackers. A comparison of lane position detection and tracking techniques is presented in [4]. One of the methods listed is described in detail in [5]. This approach uses a road model based on clothoids and tracks them by a linear vehicle dynamics model. This road model, however, encounters problems when edge detection fails in complex situations.

If detailed information on the current road is needed and when driving on urban roads, it becomes challenging to guess the road geometry in situations when line detection fails. This happens for example if road lines are occluded by other vehicles, or if the curvatures are very high. Therefore, algorithms are needed to decide which detected road lines contain useful information, which lines should be ignored, and to determine the position of road lines that were not detected at all. The advantage of our system is that additional information on the current road is provided continuously, in particular with regard to urban roads, at intersections, and exit ramps.

The road lane model presented in this paper provides a stable estimate of the current road geometry at any time. It selects suitable road lines from a vision-based lane detection system and guesses the characteristics of missing road lines by neighboring lines and a gyrosensor as illustrated in Fig. 1. For each line, a Kalman filter is used to keep track of the lateral distance to the vehicle, the heading direction, and the clothoid parameters.

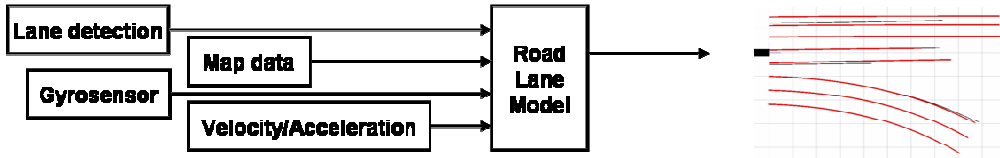


Fig. 1. Road lane model system overview

2 Road Lane Model

The road model in its current implementation keeps track of eight road lines, four on the right side and four on the left side of the vehicle. This allows providing information on at least four lanes at any time. More lines could be modeled easily, but due to their high lateral offset, they are unlikely to be recognized by lane detection systems. The benefit of modeling parallel road lines individually becomes obvious on urban streets, close to exit ramps, or at the beginning or ending of turning lanes as depicted in Fig. 2.



Fig. 2. Road lane model in selected situations

Our implementation includes Kalman filtering of the line parameters as well as a sensor fusion of the data from lane detection with the yaw rate of the gyrosensor (section 2.2). At each time step, suitable road lines from the lane detection system are selected and integrated into the current model (section 2.3). If no line is found at a certain position, we estimate the line parameters by the inner neighboring line. Since a parallel curve is needed at this step, we perform an optimization of clothoid parameters to obtain a nearly parallel clothoid even at high curvatures (section 2.4). In addition, the yaw rate sensor combined with the current map data continuously provides information on the relative movement between the vehicle and the road (section 2.5).

2.1 Basics of Clothoids

Clothoids are a special type of curve that is used for road construction to avoid abrupt changes of the steering angle when driving from straight to circular road section and vice versa. They are defined by their begin curvature c_0 , a constant curvature change rate c_1 and their total length l . The current curvature of a clothoid after length l_c equals

$$c(l_c) = c_0 + c_1 * l_c.$$

The tangent angle τ at a length l_c describes the change in orientation and is obtained by integration over l_c :

$$\tau(l_c) = c_0 * l_c + 0.5 * c_1 * l_c^2 = \frac{c_0 + c(l_c)}{2} * l_c.$$

2.2 Application of the Extended Kalman Filter

The Kalman filter is a set of mathematical equations [6]. It offers a convenient way to estimate the exact state of a technical system by drawing conclusions from defective observations. For the lane model, we use a distinct Kalman filter for each potential road line to estimate eight different parameters. The clothoid parameters c_0 , c_1 , and l , the lateral offset d_y , and the heading angle ψ are determined by the lane detection system. The heading angle represents the angle between the vehicle axis to the road. The gyrosensor combined with map data provides additional information on the yaw rate γ and the lateral acceleration of the line a_y . Therefore, the state vector for each line that we want to keep track of comprises the following parameters:

$$\hat{x}_k = (d_y \quad v_y \quad a_y \quad \psi \quad \gamma \quad c_0 \quad c_1 \quad l)^T.$$

All parameters (except the clothoid parameter) are given in relation of the own vehicle. Estimations on the current acceleration provide additional information for the velocity v_y at the next time step and also the current velocity helps to estimate the next lateral offset d_y . Similarly, the yaw rate provides information for the next yaw angle ψ and the curvature change c_1 of the clothoid is crucial to determine the curvature c_0 at the beginning of the clothoid. These connections are considered in the process function of the discrete Kalman filter that estimates the next state after a time step Δt by the parameter estimates of the current state. Due to the heading angle that we have to consider when calculating the next clothoid parameters c_0 and l , the process step of the Kalman filter is not linear and an extended Kalman filter has to be applied. In comparison to a standard Kalman filter, the extended Kalman filter provides estimates even on non-linear processes. The process function used for the road lane model relates the current state to the next state as follows:

$$f(\hat{x}_{k-1}, u_k) = \begin{pmatrix} d_y + \Delta t * v_y + 0.5 * \Delta t^2 * a_y \\ v_y + \Delta t * a_y \\ a_y \\ \psi + \Delta t * \gamma \\ \gamma \\ c_0 + \Delta t * v * \cos \psi * c_1 \\ c_1 \\ l \end{pmatrix} + \begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ -\Delta t * v * \cos \psi \end{pmatrix}.$$

2.3 Selection of Detected Lines

When road lines are detected by the lane detection system, a decision algorithm determines if the line fits into a certain position of the current road model. The main requirements are a small distance to an existing road line in the model, and suitable distances to the vehicle's center and the inner neighboring road line, whereas the suitable distance is derived from the currently observed lane width. To allow for upcoming additional lanes and ending lanes as depicted in Fig. 2, the distances to the neighboring line at the beginning or at the end of the line can be smaller.

2.4 Clothoid Parameters Estimation by Neighboring Lines

As mentioned in section 2.2, the values for a_y and γ are continuously provided by the gyrosensor and map data, but d_y , ψ , c_0 , c_1 , and l are only available if the line is detected by the lane detection system. So if a line is not detected or its current position and shape do not meet the criteria mentioned in section 2.3, we estimate the clothoid's

parameters by the parameters of the inner neighboring line. For the lateral offset and yaw angle, we restrict the values of the missing line to an appropriate range based on the values of the neighboring line. However, we have to determine the clothoid parameters c_0 , c_1 , and l in a way that the clothoid describes a parallel curve.

Since two clothoids with a curvature change other than zero cannot be parallel [7], we can only state the expected clothoid parameters and the expected change in orientation of the desired clothoid in a distance Δr . The variable c_2 denotes the curvature at the end of the clothoid and both curvature values are the reciprocal of the related radius:

$$\tilde{c}_0 = \frac{1}{\frac{1}{c_0} + \Delta r}, \quad \tilde{c}_2 = \frac{1}{\frac{1}{c_2} + \Delta r}, \quad \tilde{l} = l + \Delta r * \tau, \quad \tilde{\tau} = \tau.$$

All four conditions should be considered to obtain a suitable clothoid, particularly in case of high curvatures. If we neglect one of the parameters, the resulting clothoid may considerably differ from the desired parallel curve as demonstrated in Fig. 3. Since a clothoid has only three parameters, we used a least-squares method to determine an optimal set of clothoid parameters. After performing only a single step of the Gauss-Newton algorithm, the values converge and we observed that optimal parameters imply only minimal changes in length l and angle τ . This result corresponds to the observation made in [8], that different curvature parameters can lead to similar curve shapes.

Therefore, the results of the numerical optimization can be approximated by leaving the expected length l and change in orientation τ unchanged and by adjusting the values c_0 and c_2 . To ensure the expected change in orientation at the expected length, the sum of the begin and end curvature has to be

$$c_{0,optimized} + c_{2,optimized} = \frac{2\tilde{\tau}}{\tilde{l}}.$$

Since this differs from the sum of the expected curvature values, we add half of the resulting difference to c_0 and c_2 :

$$c_{0,optimized} = \tilde{c}_0 + \frac{1}{2} * \left(\frac{2\tilde{\tau}}{\tilde{l}} - (\tilde{c}_0 + \tilde{c}_2) \right), \quad c_{2,optimized} = \tilde{c}_2 + \frac{1}{2} * \left(\frac{2\tilde{\tau}}{\tilde{l}} - (\tilde{c}_0 + \tilde{c}_2) \right).$$

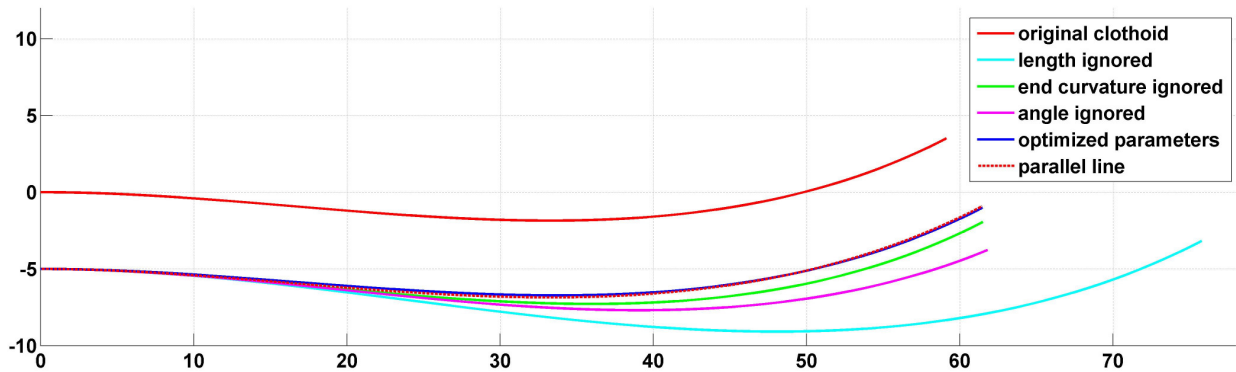


Fig. 3. Clothoid parameter estimation for a parallel line to a clothoid with $c_0=-0.01$, $c_1=0.0006$, $l=60$

An example of a clothoid with optimized curvature parameters is shown in Fig. 3. In particular for clothoids that change between positive and negative curvature or with high curvature in general, the optimization improves the resulting shape of the clothoid significantly.

2.5 Parameter Estimation by Gyrosensor

The data fusion with the gyrosensor becomes important if not a single line is identified by the lane detection system. In combination with the current speed v , acceleration a , and the expected road curvature c_r , provided by map data, information on the yaw rate γ and the lateral acceleration a_y relative to the road are available:

$$\gamma = \gamma_s - c_r * v * \cos\psi, \quad a_y = (\gamma_s - c_r * v * \cos\psi) * v * \cos\psi + a * \sin\psi.$$

In both equations, the difference between the measured yaw rate γ_s and the expected yaw rate $c_r v \cos\psi$ due to the current road curvature is needed. The result is the yaw rate relative to the current road geometry. For the lateral acceleration, the relative yaw rate needs to be multiplied with the current velocity and the heading angle ψ should be considered to get the acceleration in the direction perpendicular to the street. The effects on the road model when only the lateral acceleration is available and road lines are not detected are analyzed in detail in the following section.

3 Results

We tested the road lane model in different situations on urban roads, rural streets, and highways to ensure the stability of the model in situations when vision-based lane detection fails. Each of the evaluations depicted in Fig. 4 to Fig. 7 shows the distances of road lines to the vehicle and a comparison of the current yaw rate values. The red graphs in the upper images show the estimated lateral offsets d_y of the inner four road lines, while the black graphs represent the lateral offsets measured by the vision-based lane detection system. If a line is not detected or contains no useful information for the current road model, its black graph switches to zero. If all graphs of one color shift up or down as in Fig. 5 at $t=40s$, this indicates a lane change to the right or left respectively.

In the figures 5 to 7 we purposely ignore all detected lines for a few seconds to observe the process of the road model in comparison to the actual road lines that are still depicted in grey color. That means the model estimates the current positions of road lines solely based on the measured yaw rate and map data. Furthermore, the lower graphs show a comparison of the measured yaw rate in red color and the expected yaw rate due to the current road curvature in black. Negative values are due to a right turn, positive values follow from a turn to the left. It becomes obvious that differences between these two values affect the lateral offsets in the road lane model.

In Fig. 4 we have a common inner city situation that demonstrates the difficulties of vision-based lane detection on urban roads and particularly in tight curves. Suitable lines are not constantly detected, so that the model can only rely on single, occasionally observed lines or on the measured yaw rate and map data. In the case shown, we have a tight right curve with turn rates up to -10 deg/s . Still, the model estimates the lateral offsets qualitatively correct by continuously observing the yaw rate and selecting temporarily detected lines at $t=64s$ and $t=67s$. When several road lines are detected again after $t=70s$, all lateral offsets will be adjusted.

The next example evaluated in Fig. 5 represents a highway scenario. Due to the good visibility of road markings, the lane detection system will usually not fail. Also the map data on highways is based on the more precise Advanced Driver Assistance Systems (ADAS) quality and provides appropriate values for the current road curvature. So even if lane detection fails as simulated from $t=32s$ to $t=48s$, we can keep track of the actual distances between $t=32s$ and $t=41s$ and recognize the lane change to the right around $t=40s$. However, due to the high speed (approximately 130 km/h), the gyrosensor is sensitive to slight steering corrections as can be seen in the yaw rate image at $t=40.5s$. This causes a positive change of the lateral offsets in the road model to the extent that it erroneously assumes another lane change to the left.

On urban roads, when driving at an easy rate (approximately 50 km/h), this problem becomes less eminent. As illustrated in Fig. 6, we can detect a lane change without the mentioned effect. The model follows the actual positions of road lines for 10 seconds with a final deviation of not even $1m$. This result demonstrates the potential qualities of the model to track road markings independently from measured lines for a certain time period. To achieve this performance, the quality of the map data and the gyrosensor is crucial. Fig. 7 presents the effect of poor digitalized map data. Although the vehicle did not perform any lane change, the model wrongly estimates lateral offsets that imply several lane changes.

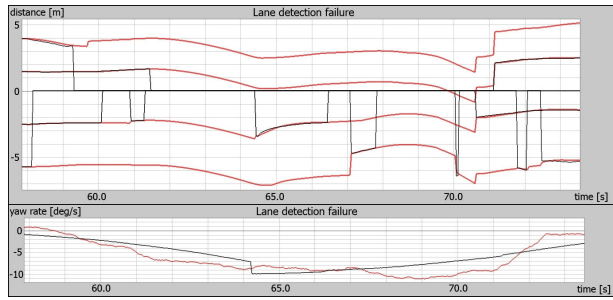


Fig. 4. Line positions and yaw rates (lane detection failure)

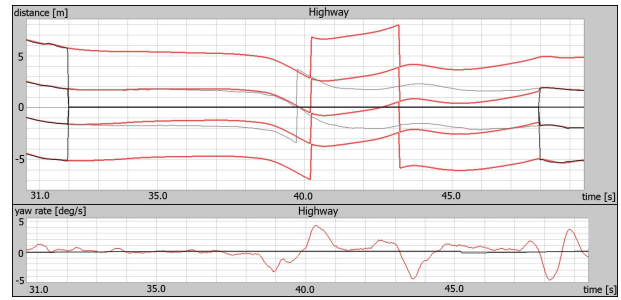


Fig. 5. Line positions and yaw rates (highway)

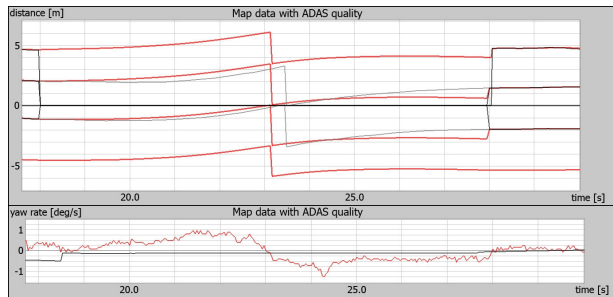


Fig. 6. Line positions and yaw rates (ADAS quality)

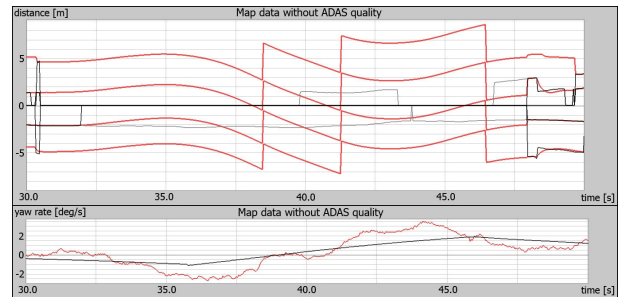


Fig. 7. Line positions and yaw rates (non-ADAS quality)

4 Conclusion

In this paper we presented the main concepts of a road lane model that keeps track of a number of parallel lanes by fusing a vision-based lane detection system with a gyrosensor, velocity, and map data. The model is based on clothoids and delivers positions, angles, and curvatures for a desirable number of parallel lines. It is robust against missing lines or erroneous detections by the vision-based system. Suitable road lines are selected by their length and distances to neighboring lines. Missing lines are estimated by numerically optimized clothoids that describe parallel curves even at high curvatures. If no lines are detected, the model can still provide plausible information by tracking the ego motion and comparing it to map data. The better this map data and the yaw rate values, the longer the model delivers plausible information. In further steps, the road geometry of map data can be improved by additional foresighted sensors. Also the yaw rate parameters may be adapted on highway scenarios to be able to deal with high velocities.

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