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A New Method for Robust Far-distance Road Course Estimation in Advanced Driver Assistance Systems

Urban Meis, *Member, IEEE* and Wladimir Klein and Christoph Wiedemann

***Abstract*— An advanced method for road course estimation is presented. It is based on the state-of-the-art Kalman filter lane detection and allows for a robust sensor-based estimation of road courses in great distances. Only the parameters for the road course are estimated which results in a reduced parameter space and therewith more robustness. Instead of laterally displaced single feature points tangential structures are used as measurements in the filter model. Therefore the method is translation-invariant and applicable for all continuous differentiable road course models. As shown with video and radar input examples it is also sensor-independent and particularly suitable for sensor fusion approaches. For accuracy estimations an advanced method based on inertial navigation is used which is independent of lateral movements of the host vehicle and the road model.**

***Index Terms*— lane detection, image processing, radar image processing, road course estimation**

I. INTRODUCTION

Nowadays driver assistance systems using lane detection for applications like lane departure warning or lane keeping are commercialized. In general those systems use monocular cameras and are able to detect lanes or road courses up to a range of about 60 meters. When it comes to next generation applications like lane keeping or continuous lateral control (e.g. lane centering) more sophisticated and robust methods are necessary to fulfill the requirements in availability, accuracy and detection range. State-of-the-art lane detection systems can measure the lane up to a short range. For control systems that support velocities up to 200 kilometers per hour this range has to be increased. Furthermore the state-of-the-art systems relate the lane information to the sensor's origin or the car's front axle and the road course ahead of the host vehicle is just predicted. The standard approach comprises a clothoidal model approximated by a polynomial [1] [2]. Methods for modeling the road three-dimensionally have been proposed using monocular [3] and stereo [4] [5] vision. To model road shapes in complex scenarios or covering a large stretch spline models [6] [7] and series of circular arcs [8] [9] or clothoids [10] have been introduced. To increase the range for road course estimation radar sensor methods were introduced [11] [12] [13] and fusion approaches were presented [14] [15] [16] including additional digital map information [17] [7]. Methods for using other features than lane markings like pavement borders or crash barriers were presented [18]. Many of the approaches fusing different types of information are based on particle filters [19] [20] [7] [18] [16] to be able to use any kind of cues in non-linear measurement functions. Particle filter approaches tend to consume a huge amount of computational costs as the parameter space has to be covered with samples.

The main problem in using the standard approach in great distances is the necessity to determine the side of the road for each feature and especially the exact distance to the skeleton line of the host vehicle. Wrong decisions could lead to quite misleading estimations. E.g. parallel structures to the lane markers like crash barriers or pavement borders have different offsets to the skeleton line. The bigger the distance to the sensor the noisier and sparser the measurements get. Here a method is presented which copes with this problem in being independent of the side and the lateral distances of the features. With longer distances to measure and estimate the need arises to use more complex road models. The presented method is applicable for all continuous differential models. It is able to fuse input of different sensors. In this paper the method is applied and evaluated for monocular video and high-resolution radar.

To evaluate road course estimation ground truth data is needed. To avoid using expensive equipment and to be able to get huge amounts of data, inertial navigation using "Dead Reckoning" was introduced for evaluation in automotive applications [21] [22]. Dead Reckoning uses the recorded velocity and yaw rate of the host vehicle's motion and rotation sensors to calculate its driven trajectory. Those sensors are usually available and sufficiently accurate in today's production vehicles. The trajectory is compared piecewise to the estimated road course. The drawback is that lateral movements of the car introduce an additional error to the evaluation. To overcome this the usage of the lateral offset of the lane estimation in the dead reckoning process was introduced [22]. An improvement of this method is presented here, being independent of a certain road model.

II. METHOD

A commonly used lane model [3] approximating the road course's clothoidal curvature form with a polynomial of third degree is:

$$y_f = \frac{1}{2}w + y_v + \tan\psi_v x + \frac{1}{2}c_0 x^2 + \frac{1}{6}c_1 x^3. \qquad (1)$$

The measurement feature position y_f contains the offset to the skeleton line of the host vehicle. The width of the lane w and the lateral offset of the host vehicle to the lane center y_v

U. Meis and W. Klein and C. Wiedemann are with Advanced Driver Assistance Systems of A.D.C. Automotive Distance Control Systems GmbH, a subsidiary of Continental AG, 88131 Lindau, Germany urban.meis@continental-corporation.com, wladimir.hellmann@continental-corporation.com, christoph.wiedemann@continental-corporation.com

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are a different representation for distances to the left and right lane boundary (d_l,d_r). For small heading angles ψ_v of the vehicle to the road tangent (up to $15°$) the approximation of the angle in radiants is very close to the first order polynomial parameter, because the cosine and the sine are close to 1 and its argument. Therefore the tangent of ψ_v can be omitted. c_0 and c_1 describe the curvature at the actual position of the host vehicle and the change of curvature in the viewing range. In this paper coordinate systems are always according to ISO8855. Based on this model, the feature generation and selection process for video and radar is depicted first. Then it is described how these features are used in the new measurement method.

A. Pre-processing

The first step in this method is to reduce the complexity of the road model and to split the lane parameters in partitions with parameters relevant for the near and far range. This partitioning of the road model's parameter space is vital for detection ranges up to 200 meters. The measurements for the width of the lane, the offset and the heading angle of the host vehicle to the lane center are most accurate in the near range. Those parameters are most relevant for lane departure warning or lane keeping where the distances of the front wheels to the road or lane borders have to be accurate. The width may also vary in a viewing range of 200 meters, e.g. in lane widenings or narrowings. Filtering those parameters with features in great distances will lead to inaccuracies and reduce the performance of the system. Additionally, especially in the radar case, different structures parallel to the lane may be detected and not recognized. E.g. in the near range curbs and crash barriers are detected whereas in the far region lateral slopes, walls and other natural or artificial borders are dominant. Using only the parameters describing the road course in the far region all lane-parallel structures can be included as input without estimating the lateral distances of the different structures. Hence, the distance to the left and right road borders and the host vehicle's yaw angle constitute the partition $\mathbf{P_p}$ describing position and direction (posture) of the host vehicle in the lane and curvature and change of curvature constitute the partition $\mathbf{P_c}$ describing the road course.

$$\mathbf{P_c} = \{c_0, c_1\}, \mathbf{P_p} = \{d_l, d_r, \psi\} \tag{2}$$

For partitioning in lane detection see also [19][17].

In fig. 1 the main processing steps are shown. The filter module for the road course partition is an add-on to the posture partition estimation, which is done by a state-of-the-art lane detection approach. The additional far feature generation is explained briefly and the focus is on the far region filtering, which is capable of integrating tangential features of different structures and sensors.

B. Feature generation

1) Video based: In case of video based lane detection a conventional lane detection system is used to determine the parameters of the posture partition and also to narrow down the region of interest for the course partition (see fig. 2). Hence, the search window is very small and though the image processing is very efficient. From the conventional lane detection system the projective transformation for image positions to road plane coordinates is also considered as given. This leads to a linear filter model for the road course partition and a standard Kalman filter can be used.

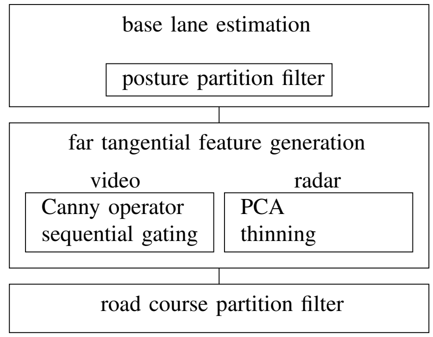

Fig. 1. Module flowchart

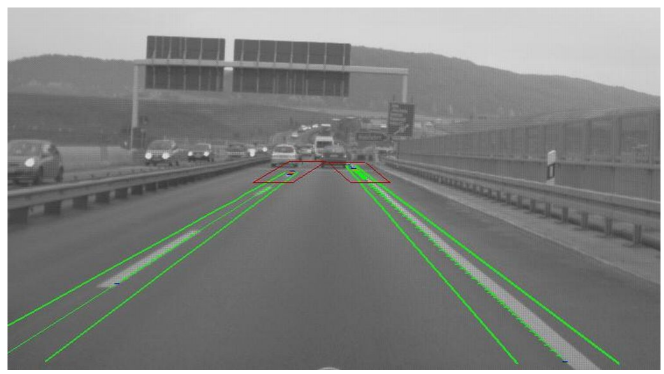

Fig. 2. Video feature extraction: regions of interest extrapolated based on near range lane detection are depicted in red; green colored road course estimation from the conventional lane detection algorithm

As this paper focuses on the measurement method and modeling, the feature generation is only described shortly. The near region lane detection provides estimates of the posture partition $\mathbf{P_p}$ based on image features. It also includes the projective transformation. These parameters and the furthermost selected features of the near range are used to determine the region of interest for the road course estimation (fig. 2). For each side a search window is set starting in 35 meters and allowing for the detection of curvature radii down to 100 meters. Image features are generated using x- and y-Sobel gradient filters in the search windows. The gradient's magnitude and discretized orientation are processed with a Canny operator that clusters connected edge structures to further narrow down the selection. Remaining features containing the continuous gradient orientation are transformed into the road plane for further data association. The projected gradient orientations are assumed to be tangential to the road course and are represented by their position x, y and slope m in the road coordinate system. The final data association process of tangential features $f_i = (x_i, y_i, m_i)$ to the filter measurement step is depicted in fig. 3. The features are considered for the measurement update if the distance df to the initial curvature calculated by the already selected m_1 and the candidate m_2 is smaller than a given ϵ. This selection process is done sequentially starting with the furthermost features of the near range filter.

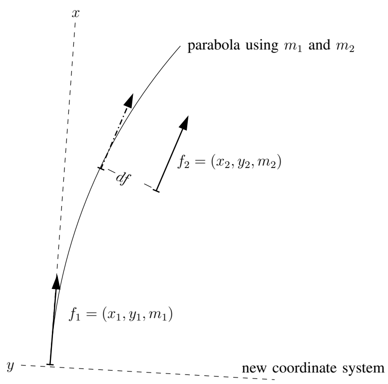

Fig. 3. Video feature extraction: select candidates; measurement features $f_i = (x_i, y_i, m_i)$ are selected according to their distance df to the curvature calculated by m_1 and m_2

The slopes m_i of the remaining features f_i are used directly in the Kalman filter update.

2) Radar based: Due to the sensor measurements in the road plane coordinate system a standard linear Kalman filter can be applied for both partitions. The partitioning is realized using two different measurement updates. Again the feature generation is described rudimentary as the focus is on the measurement method. As input for the road estimation a list of stationary targets is used and clustered into connected components. A principle component analysis provides the orientation and centroid of the clusters and therewith first tangential features. Afterward the clusters are thinned out, so that only inner features from the sensor origin point of view remain (see fig. 4).

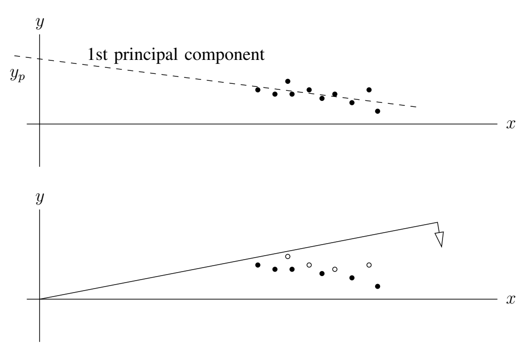

Fig. 4. Coordinate system with measurement examples; intersection y_p of the cluster's first principal component with the y-axis; remaining inner feature points according to selection process

The y-axis intercept y_p of the first principal component of the cluster indicates the side from where the sensor detects the structure. Features are represented by their angle to the vehicle's longitudinal axis and the distance. For each target more distant targets with greater angles according to the detection side are not considered for the measurement update.

Pairs of remaining cluster targets and their segment center provide additional feature candidates $f_i = (x_i, y_i, m_i)$. In the data association step outliers according to their orientation are eliminated.

Fig. 5. Radar feature extraction: corresponding video scene; clustered stationary targets in bird eye view; associated tangents depicted in green

In fig. 5 the feature generation process with resulting tangential measurements is depicted.

C. Measurement model

The relevant parameter set for the filter model is equal to the road course partition $\mathbf{P_c} = \{c_0, c_1\}$. As features and the model are described in road plane coordinates a general linear Kalman filter is used. All matrices are presented in a time discrete form. The innovation presented in this paper is to use tangents directly as features for a simple Kalman update.

1) Video based: The equations for the measurement update step are as follows:

$$m_{i,t} = c_{0,t} x_{i,t} + \frac{1}{2} c_{1,t} x_{i,t}^2 \tag{3}$$

The measurement model uses the fact that the first derivate of the lane model (eq. 1) equals the slope of the tangential features at position x. Here the heading angle of the vehicle is omitted, because it is already calculated in the conventional lane detection algorithm. The general measurement model is

$$z_t = \mathbf{H_t} q_t + \nu_t \tag{4}$$

with

$$z_t = \begin{pmatrix} m_{0,t} \\ \vdots \\ m_{n,t} \end{pmatrix}$$

and

$$\mathbf{H_t} = \begin{pmatrix} x_{0,t} & \frac{1}{2}x_{0,t}^2 \\ \vdots & \vdots \\ x_{n,t} & \frac{1}{2}x_{n,t}^2 \end{pmatrix}$$

and

$$q_t = \begin{pmatrix} c_{0,t} \\ c_{1,t} \end{pmatrix}$$

The measurement noise vector ν_t is dependent on the x-position and the predicted slope at this position. For the prediction step the following state transition is used:

$$\mathbf{A_t} = \begin{pmatrix} 1 & \Delta t \cdot v_{x,t} \\ 0 & 1 \end{pmatrix}$$

As the measurements are independent iterative update steps can be used:

$$z_{i,t} = h_{i,t} q_t + \nu_t \tag{5}$$

with

$$z_{i,t} = m_{i,t}$$

and

$$h_{i,t} = \begin{pmatrix} x_{i,t} & \frac{1}{2}x_{i,t}^2 \end{pmatrix}$$

This approach significantly simplifies the measurement model. Measurements are still one-dimensional and the state vector to be updated is only two-dimensional.

2) Radar based: In contrast to the image features the radar features and the complete road model are already in ground plane coordinates. Hence, the Kalman filter is linear and the state vector contains both partitions $\mathbf{P_p}$ and $\mathbf{P_c}$:

$$q_t = \begin{pmatrix} d_{l,t} \\ d_{r,t} \\ \psi_t \\ c_{0,t} \\ c_{1,t} \end{pmatrix}$$

In the measurement step only the parameters of partition $\mathbf{P_c}$ are updated:

$$m_{i,t} = \psi_t + c_{0,t} x_{i,t} + \frac{1}{2} c_{1,t} x_{i,t}^2 \tag{6}$$

and

$$h_{i,t} = \begin{pmatrix} 0 & 0 & 1 & x_{i,t} & \frac{1}{2}x_{i,t}^2 \end{pmatrix}$$

Again the first derivate of the lane model (eq. 1) is used including the heading angle, which does not contribute to the Kalman gain. For the prediction step the following state transition is used:

$$\mathbf{A_t} = \begin{pmatrix} 1 & 0 & \Delta t \cdot v_{x,t} & \frac{1}{2}\left(\Delta t \cdot v_{x,t}\right)^2 & \frac{1}{6}\left(\Delta t \cdot v_{x,t}\right)^3 \\ 0 & 1 & \Delta t \cdot v_{x,t} & \frac{1}{2}\left(\Delta t \cdot v_{x,t}\right)^2 & \frac{1}{6}\left(\Delta t \cdot v_{x,t}\right)^3 \\ 0 & 0 & 1 & \Delta t \cdot v_{x,t} & \frac{1}{2}\left(\Delta t \cdot v_{x,t}\right)^2 \\ 0 & 0 & 0 & 1 & \Delta t \cdot v_{x,t} \\ 0 & 0 & 0 & 0 & 1 \end{pmatrix}$$

For the reason of simplification the yaw rate is left out. The state transition for the road course parameters are the same as in the partitioned case and the yaw rate does not alter the transition. For sensor and information fusion on a feature level the partitioned variant would be selected and all features in the distance-slope representation can be used.

III. EVALUATION

A. Evaluation method

In inertial navigation motion and rotation sensors are used to calculate the driven trajectory of the host vehicle. This process is called ”Dead Reckoning”. In evaluation for automotive road course estimation it is used as a simple method to generate ground truth data for huge amounts of data. The recorded velocity and yaw rate are used to calculate a driven trajectory of the host vehicle in retrospect [21], which is corrected by the lateral offset of the lane detection to generate the ground truth road course [22]. Also in [22] it was shown that the usage of the near range lane estimation parameter offset is sufficiently accurate to be used for the ground truth calculation. The parameters of the road course measurement at a given time stamp or location are compared to the retrospectively calculated ground truth parameters of the ground plane window that is used for the measurement. This method is especially well suited when just regarding road course parameters and not e.g. the width of the road. Instead of generating a road model based approximation from the calculated trajectory as ground truth, the recorded distances to the left and right lane boundary are used as ground truth for each distance sample position that is evaluated. By using those sample distances the evaluation method is independent of the road model.

The recordings provide velocity, yaw rate and the lane measurement for each sample time in set T:

$$T = \{0, \ldots, t_e\} \tag{7}$$

For each time step evaluations for sample distances in x-direction are performed. The sample distances m are listed in the set $\mathbf{M} = \{15, 30, 45, 60, 100, 150\}$. The coordinate system is reset for each evaluation time sample.

The evaluation window for each measurement and evaluation sample position in M uses a subset of T:

$$T_{s,k} = \{t_s, \ldots, t_k\} \subseteq T \tag{8}$$

The window starts at t_s and the sample time t_k indicates the sample where the host vehicle traveled more than the distance m of M in x-direction.

In fig. 6 the evaluation sample distance of $60m$ is depicted. The sample times are selected so that the exact sample position can be interpolated. The position and orientation

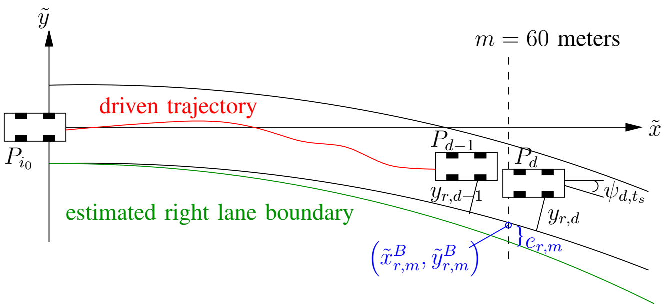

Fig. 6. Dead Reckoning procedure: For each road course measurement ground truth sample positions are calculated; here for example in a distance of 60 meters; the ground truth position $\left(\tilde{x}^B_{r,m}, \tilde{y}^B_{r,m}\right)$ is generated by first calculating the vehicle's position and orientation using yaw rate and speed; then the measured distances of the posture partition filter are included and at last an interpolation at $x = 60m$ is performed; these ground truth positions are compared with samples of the estimated road course model

of the host vehicle are calculated at each distance sample position in the new coordinate system. The host vehicle's yaw angle for all sample times in $T_{s,k}$ relative to the angle at time t_s is calculated. For $t_s + i$ it is:

$$\psi_{i,t_s} = \sum_{\tau=t_s}^{i} \dot{\psi}_\tau \Delta t_\tau, i \in T_{s,k} \tag{9}$$

Then the vehicle's position is calculated in the evaluation sample distance m at the neighboring sample times t_k and t_{k-1}:

$$\tilde{x}^{\text{veh}}_{i,t_s} = \sum_{\tau=t_s}^{i} \cos(\psi_\tau) v_\tau \Delta t_\tau, i \in \{t_{k-1}, t_k\} \tag{10}$$

$$\tilde{y}^{\text{veh}}_{i,t_s} = \sum_{\tau=t_s}^{i} \sin(\psi_\tau) v_\tau \Delta t_\tau, i \in \{t_{k-1}, t_k\} \tag{11}$$

The recorded distances $d_{l,r}$ to the left and right border of the lane are normal to the vehicle's yaw angle at these positions and determine ground truth coordinates of the left and right lane boundary. They are interpolated at the evaluation sample distance m for each side resulting in the ground truth boundary points $\left(\tilde{x}^B_{l/r,m}, \tilde{y}^B_{l/r,m}\right)$.

The error f for a evaluation time sample and a sample distance m is calculated as follows:

$$e_{l/r,i} = d_{l/r,t_s} + \psi_{t_s} i + \frac{1}{2} c_{0,t_s} i^2 + \frac{1}{6} c_{1,t_s} i^3 - \tilde{y}^B_{l/r,i}, i \in M \tag{12}$$

$$f_i = \frac{1}{2}\left(e_{l,i} + e_{r,i}\right), i \in M \tag{13}$$

All error measurements are gathered in a distribution for each sample distance m. Their Gaussian distribution parameters μ and σ are evaluated. The evaluation sampling in different distances implies independence of a road model. So different road models for the road course estimation can be evaluated.

B. Experimental results

The method of tangent updates is compared to single positional updates. To allow for the comparability of the new measurement approach to the classical, in this evaluation the

TABLE I

VIDEO: DETECTION RANGES FOR MARKER TYPES

marker type	continuous [%]	dashed [%]
occurrence	53.5	39.1
10 m	100.0	100.0
20 m	100.0	100.0
30 m	99.9	99.8
40 m	92.5	88.1
50 m	68.2	49.2
60 m	45.1	16.7
70 m	26.6	1.4
80 m	9.0	0.3
90 m	3.2	0.0

TABLE II

VIDEO: ACCURACIES

at	classical μ [m]	new method μ [m]	classical σ [m]	new method σ [m]
15 m	0.005	0.003	0.101	0.101
30 m	-0.008	-0.010	0.164	0.161
45 m	-0.047	-0.037	0.184	0.200
60 m	-0.034	-0.039	0.200	0.188

tangential features are gathered using the feature positions of the classical approach. This leads to the same detection ranges and the same general availability of 95%.

1) Video data: For the evaluation in the video case a recording of a 22.2 kilometer drive on a country road was used. In tab. I the detection ranges depending on marker types are depicted.

Generally the detection range is reduced in winding country road scenarios. Also the ranges for continuous markers are greater because of the increased feature density in the far-distance and the better predictability when using the conventional lane detection results to narrow down the search window.

The accuracy evaluation in tab. II shows that both methods are comparable. Hence, the simplified and more efficient new approach does not imply any loss in accuracy. Additionally extending the range of the conventional method leads to inaccuracies in the near area which is relevant for lane departure warning and lane keeping applications.

2) Radar data: For the evaluation in the radar case a recording of a 1.2 kilometer drive on a winding highway was used. The both-sided availability was 90% and the system's detection range is up to 200 meters.

In tab. III it is shown that the accuracy of the new approach using tangential updates is much better. The mean difference μ is half the difference of the classical method and even in a distance of 150 meter less than a meter. This allows for a better association of objects to lanes, which is relevant for adaptive cruise control functions. Additionally the effect of structures having different offsets to the center of the road is reduced, because only the orientations of these structures are used.

TABLE III

RADAR: ACCURACIES

at	classical μ [m]	new method μ [m]	classical σ [m]	new method σ [m]
15 m	0.093	0.057	0.427	0.400
30 m	0.205	0.123	0.710	0.636
45 m	0.372	0.187	0.931	0.814
60 m	0.508	0.240	1.141	0.960
100 m	0.950	0.317	1.606	1.274
150 m	1.662	0.811	1.757	1.256

IV. CONCLUSIONS AND FUTURE WORKS

A. Conclusions

This method is an advancement of the state-of-the-art Kalman filter lane detection and allows for a robust sensor-based estimation of road courses in great distances. Only the parameters for the road course are estimated, which results in a reduced parameter space and therewith more robustness and efficiency. Instead of lateral displaced single feature points tangential structures are used as measurements in the filter model. Therefore the method is translation-invariant and applicable for all continuous differentiable road course models. As shown with video and radar input examples it is also sensor-independent and well suited for sensor fusion approaches. For accuracy estimations an advanced dead reckoning method is used which is independent of the road model. The method shows potential for improving adaptive cruise control applications and also for lane departure warning and lane keeping functions in increasing the detection range and not affecting the near-area.

The main problem when fusing data of different sensors is the correlation of those data types. Especially video and radar sensors detect different structures like lane markings and crash barriers with different lateral offsets to the skeleton line of the road. With this method the orientation of structures detected by any kind of sensor is used as measurement in the filter model and consequently it is independent of the lateral offset. Tangents of all structures that are parallel to the road course could be used in this method (e.g. reflection posts, crash barriers, lane markings, road curbs). So it could also be used for multi-cue data fusion. As each tangent measurement is equivalent to the curvature at this distance they indicate the end of the clothoid or the point of transition to the next clothoid. Hence, with this method the systems becomes able to predict road's curvatures in advance.

B. Future Works

Additional video features that are parallel to the road course are going to be used to improve the availability in unmarked scenarios and the robustness in complex scenes. Also the method will be investigated for sensor fusion approaches. To further support lateral control systems the capability to determine the transition of road segments will be investigated. More complex road models like double clothoids and splines will be used for winding country road scenarios.

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