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Using digital maps to enhance lane keeping support systems

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Abstract— **The development of a system that can be used for a safe, reliable, highly available onboard lane keeping support system is a critical research topic. One of the most important functions in driver assistant systems is the detection of unintentional lane departures. Current lane departure warning systems focus mainly in the detection of lane markings using vision sensors, such as CMOS cameras. In order to increase accuracy and robustness of such systems the utilization of digital maps is necessary. The goal of combining camera and map data is to extend the road geometry in further distances and eliminate false alarms based on unintentional maneuvers caused by the driver. The overall system efficiency is increased furthermore by using also vehicle dynamics and road geometry calculated using radar data.**

I. Introduction

ROAD safety can be increased by using lane departure warning systems, that inform the driver in the case the vehicle is leaving the ego lane and is entering one of the adjacent lanes. Nowadays, existing systems are capable only in detecting lane changes but not to recognize the intention related with the maneuver. In the future more active systems should be capable of detecting non-intentional departures and then to cause opposite force to the steering system in order to reinstate the vehicle to the initial lane. Using these systems accidents in the lateral field of the vehicle can be avoided increasing the overall safety in the road. Field operational tests have shown that a large amount of traffic fatalities and injuries can be avoided by using such systems [1], [5].

Current research efforts focus in satisfying the requests for developing a system that works under various road and driving conditions [2], [3]. This means that the system must be capable of dealing with situations where lane markings are missing or ambiguous, or the visibility is restricted due to weather conditions that limit the performance of vision sensors. Other factors that must be taken into account are the additional traffic, the driver intention or complex situations like overtaking. The main application field is the driving of commercial- and passenger vehicles, like trucks and cars, on motorways and rural roads. The functional development in such systems is accompanied by investigations aiming at a unification process for lane keeping support systems.

The goal of this paper is to enhance previous developed systems using vision sensors by utilizing multiple sources of information resulting in a situation-adaptive system for enhanced lane keeping support. This can lead to the development of the technology for a safe, reliable, highly available, acceptable and legally admissible onboard lane keeping support system for use in commercial and passenger vehicles on motorways and rural roads. The system reaction in critical lane departure situations comprises the control of warning actuators and an active steering actuator.

The proposed system includes except from a CMOS camera, also a positioning system utilizing digital maps, radar for detecting traffic and on-board inertial sensors for estimating ego vehicle dynamics. The camera provides the road geometry using a clothoid model. The positioning unit provides the most likely path as a list of shape points. A shape point includes the geographical coordinates of a specific point of the road and is retrieved from the map data database. This path is the most probable route that the vehicle is about to follow. The radar sensor provides all the tracked objects that are moving inside the road. Finally using the inertial sensors the curvature of the road is calculated supposing that the vehicle is not performing complex manoeuvres.

The paper is organized as follows: In Chapter 2, the algorithm for estimating the road geometry is introduced, whereas in Chapter 3 the lane data fusion method is presented using the four sources of information described above. The algorithm that is presented for the road estimation using the map data is extending the existing techniques that are used in applications using cameras or radars for estimating road geometry by using multiple clothoids in order to increase the accuracy in greater distances. Results regarding the performance and the evaluation of the algorithms are presented in Chapter 4. To

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evaluate the performance of the proposed algorithms real data were used coming from a truck equipped with the sensors described above.

II. Road Geometry Calculation Using Digital Maps

A. Introduction

The positioning unit is using a digital map database to extract information about road segments lying ahead of the vehicle. The output of this procedure is called the "Electronic Horizon" and it includes all the possible routes that the vehicle can follow. The Electronic Horizon can be used to extract the most likely path which is the path with the higher probability regarding the intention of the driver to choose it between all the possible branches of the road. The main objective is to calculate the trajectory that best fits to the actual road that the vehicle is about to cross using the list of shape points that describe the most likely path. The processing includes transformation to the local coordinate system, grouping of the points according to specified rules and filtering of data to extract the parameters that describe the road geometry. The processing steps are shown in the next figure.

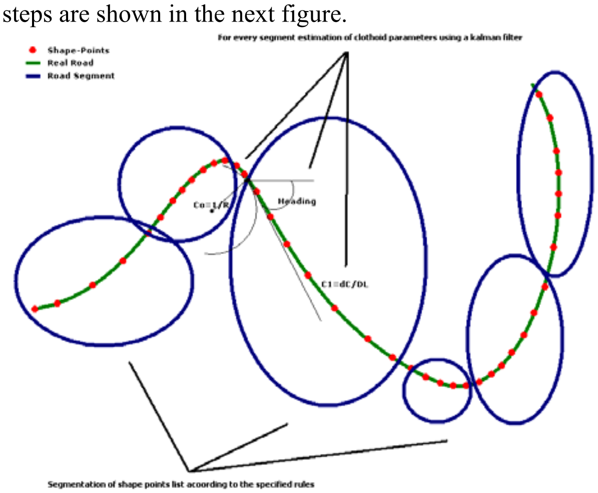

Fig. 1. Scheme for estimating road geometry using map data

The shape points formulating the most likely path (green line) are the red dots and the blue circles are indicating the segments in which the road is split.

B. Algorithm

The mathematical model that is used for describing the geometric properties of the road is the clothoid model and is given from the following equation:

$$y = y_0 + th \cdot x + \frac{c_0}{2} \cdot x^2 + \frac{c_1}{6} \cdot x^3 \tag{1}$$

$$c = c_0 + c_1 \cdot l \tag{2}$$

where c_0, c_1 is the curvature and curvature rate respectively and th is the tangent of the heading angle in the beginning of the road segment. Due to the very long road lengths ahead of the vehicle it has to be considered the use of multiple clothoid filters in order to acquire a more accurate prediction of the road geometry.

The algorithm for estimating the road borders includes the following steps. First, the transformation from the geodetic coordinate system to the Earth – fixed Earth – Centered (ECEF) coordinate system. Then it is following the transformation from the ECEF system to the local tangential system which is a Cartesian coordinate system. The equations used for the first transformation are the following:

$$\begin{aligned} X &= (N+h) \cdot \cos(\lambda) \cdot \cos(\phi) \\ Y &= (N+h) \cdot \cos(\lambda) \cdot \sin(\phi) \\ Z &= \left[N \cdot (1-e^2) + h\right] \cdot \sin(\lambda) \end{aligned} \tag{3}$$

where e is the eccentricity of the ellipsoid (for WGS-84, $e = 0.0818$) and

$$N(\lambda) = a \Big/ \sqrt{1 - e^2 \cdot \sin^2(\lambda)} \tag{4}$$

The equations for the second transformation are the following:

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = L \cdot \left(\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} - \begin{bmatrix} X_0 \\ Y_0 \\ Z_0 \end{bmatrix} \right)$$

$$L = \begin{bmatrix} -\sin(\varphi) & \cos(\varphi) & 0 \\ -\sin(\lambda) \cdot \cos(\varphi) & -\sin(\lambda) \cdot \sin(\varphi) & \cos(\lambda) \\ \cos(\lambda) \cdot \cos(\varphi) & \cos(\lambda) \cdot \sin(\varphi) & \sin(\lambda) \end{bmatrix} \tag{5}$$

Secondly the segmentation of the list containing transformed coordinates of shape points. This task is performed according to a set of rules regarding the total length and density of the segments that are going to be created. More specifically the segmentation is performed according to the following steps:

1) The shape points are divided to segments according to the local maximums and minimums in both dimensions.
2) Every segment is further divided by using a threshold for the maximum length of a segment.
3) In the next step segments with a low density of shape points, like in the case of a straight road are united in one segment.
4) In the final step in order to ensure the continuity between successive segments, two shape points in the beginning of every segment are assigned also to the previous segment.

In each segment the heading angle is estimated geometrically at the beginning of it. Then all the coordinates of the shape points are transformed to the new coordinate system that has its center located to the first shape point and its x axis parallel to the initial heading.

The output of the segmentation is a list with shape point segments which is defined as:

$$S_i = \begin{Bmatrix} x_j \\ y_j \end{Bmatrix}$$

$$i = 1, \dots, N \quad j = 1, \dots, L_i \tag{6}$$

where N is the number of segments and L_i is the length of $i-th$ segment.

Finally, Kalman filtering is applied for estimating road parameters using the clothoid model. For this purpose a bank of Kalman filters is used, in which the filters are identical and have the following parameters. The state vector of the filter is the parameters of the clothoid equation.

$$x_i = \begin{bmatrix} y_0^i & th^i & c_0^i & c_1^i \end{bmatrix}^T \tag{7}$$

The measurement vector includes all the $y-$coordinates of the shape points belonging to the specific segment and is the following:

$$y_i = \begin{bmatrix} y_{i,1} & \dots & y_{i,L_i} \end{bmatrix}^T \tag{8}$$

The transition matrix is the following:

$$A_i = \begin{bmatrix} 1 & dx & dx^2/2 & dx^3/6 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & \sqrt{dx^2 + dy^2} \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{9}$$

where (dx, dy) is the translation of ego vehicle in both axes and is given by the following equations:
As it can be seen the update model that was chosen for the offset and curvature is the clothoid (1), (2) respectively and for the heading and curvature rate a constant update model.

The measurement matrix is:

$$C_i = \begin{bmatrix} 1 & x_{i,1} & x_{i,1}^2/2 & x_{i,1}^3/6 \\ 1 & x_{i,2} & x_{i,2}^2/2 & x_{i,2}^3/6 \\ \vdots & \vdots & \vdots & \vdots \\ 1 & x_{i,L_i} & x_{i,L_i}^2/2 & x_{i,L_i}^3/6 \end{bmatrix} \tag{10}$$

Finally the process Q_i and R_i measurement noise covariance matrices are respectively:

$$Q_i = q \cdot S \cdot q^T \tag{11}$$

$$R_i = \begin{bmatrix} \sigma_{y,1}^2 & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & \sigma_{y,L_i}^2 \end{bmatrix} \tag{12}$$

where:

$$q = \begin{bmatrix} dx & dx^3/6 \\ 1 & 0 \\ 0 & \sqrt{dx^2 + dy^2} \\ 0 & 1 \end{bmatrix}$$

$$S = \begin{bmatrix} \sigma_h^2 & 0 \\ 0 & \sigma_{cr}^2 \end{bmatrix} \tag{13}$$

where $\sigma_{y,1}, \dots \sigma_{y,L_i}$ are the standard deviations of the measured y coordinate of shape points and $\sigma_{th}, \sigma_{c_1}$ are the standard deviations of the heading and curvature process noise respectively. In order to evaluate the efficiency of the algorithm the final output is accompanied with a confidence value for every segment which is calculated as followed:

$$\sigma_M = \frac{\sigma_M^2 - \sigma_{M,MIN}^2}{\sigma_{M,MAX}^2 - \sigma_{M,MIN}^2} \cdot (n/N_{SP}) \tag{14}$$

where σ_M^2 is the variance of the estimated variance, n is the number of shape points forming the segment and N_{SP} is the maximum number of shape points allowed.

III. Lane Data Fusion

A. Introduction

The role of this module is very important as it is leading in increased robustness of the overall system and is extending the detected lanes by the camera sensor to greater distances using information from the positioning unit [7]. Cases where the camera fails to detect the lane markings due to restricted visibility or ambiguous markings can now be handled using a special filter which keeps estimating the offset and updates the rest of the parameters from the map data. Also in normal conditions the final estimation is refined as the module combines the camera data in lower distances with the map data in greater distances.

B. Algorithm

The main fusion algorithm is performed using the processed data coming from the vision sensor which are delivered in the form of clothoid parameters. The other source of information is the lane attributes delivered by the electronic horizon of the positioning unit as described in the previous section. The core of the algorithm for fusing the lane attributes is described in the following section and is the following:

1) If both camera and map data are available then the final output is a combination of this two sources of information.

2) If only one of these two sources is available the final output is equal to it.
3) If none of the camera or map data are available then the final output is a combination of the geometry extracted using the radar data and the vehicle dynamics.

Because the offset of the vehicle from the lane marking is provided only by the vision sensor, a special lateral Kalman filter is used in the case that camera data are not available. This filter continues to provide estimations of the offset for a specific amount of time when there is a failure of the vision sensor. The time threshold T_{LF} which defines the capability of the filter to provide lane offset estimations continuously without measurements is set usually below 2 seconds. The state and measurement vectors of this filter are the following:

$$x = \begin{bmatrix} y_0 & V_L & A_L & w \end{bmatrix}^T \tag{15}$$

$$y = \begin{bmatrix} y_0^{cam} & w^{cam} \end{bmatrix}^T \tag{16}$$

where y_0 is the offset from the middle of the lane where the vehicle is moving and w is the width of this lane. y_0^{cam}, w^{cam} are the offset and width provided by the camera respectively. V_L, A_L are the lateral velocity and acceleration of the vehicle (first and second derivative of the offset) respectively. For the three first states a constant acceleration model is used while for the last state (width) a constant state model is used.

The combination of the camera and map data in order to extract the final trajectory that best describes the road is done using the following equations.

$$\begin{aligned} y_f &= w_C \cdot y_C + w_M \cdot y_M \qquad x \le d_C \\ y_f &= y_M \qquad\qquad\qquad\quad\; x > d_C \end{aligned} \tag{17}$$

where y_C, y_M, y_f are the camera, map and fused trajectories respectively. d_C is the maximum distance of the camera trajectory. w_C, w_M are the weights for the camera and the map geometry respectively and are given from the following equations:

$$\begin{aligned} w_C &= \sigma_C / (\sigma_C + \sigma_M) \\ w_M &= \sigma_M / (\sigma_C + \sigma_M) \end{aligned} \tag{18}$$

where:

$$\sigma_C = \frac{\sigma_C^2 - \sigma_{C,MIN}^2}{\sigma_{C,MAX}^2 - \sigma_{C,MIN}^2} \cdot (x/d_C) \tag{19}$$

where σ_C^2 is the variance of the estimated curvature from the camera and x is the distance from the ego vehicle. σ_M is the confidence calculated for the first segment of the map data (14). The main weight for the camera and the map data is based on the variance of the estimated values. When the variance is increasing then less confidence is assigned to the specific source of information. Also, the distance from the ego vehicle is regarded. As the distance is increasing, more weight is assigned to the map data than to the camera as the estimation error for the camera is getting very big for large distances ahead and more specifically for distances greater than 50m or 60m.

When there is no map or camera data then the road geometry is given from the following equations:

$$\begin{aligned} y_f &= y_{EV} \qquad\qquad\qquad x \le d_{EV} \\ y_f &= \sum_{i=1,\dots,N_R} w_R^i y_R^i \qquad x > d_{EV} \end{aligned} \tag{20}$$

where d_{EV} is a distance threshold and N_R is the number of objects detected by the radar. The curvature and curvature rate in the case of the radar objects is calculated using polynomial fitting to the buffer which holds all the previous locations of the objects. The curvature using vehicle dynamics is calculated using the following formula:

$$c_0 = \omega / V \qquad c_1 = 0 \tag{21}$$

where ω, V are the yaw rate and velocity of the ego vehicle provided by the can bus. The weight w_R^i for the radar object is calculated as:

$$w_R^i = \sigma_R^i \Big/ \sum_{j=1}^{N_R} \sigma_R^j \tag{22}$$

In both cases the offset in order to calculate the lateral displacement y using the clothoid model is provided from the lateral filter described above.

IV. Results

The algorithms have been implemented in C++ and have been tested using real data acquired using an experimental truck equipped with a camera for lane detection, a radar for traffic detection, a positioning unit with digital maps and inertial sensors for vehicle dynamics estimation.

The application of the road geometry estimation algorithm using maps, applied in a specific scenario, is presented in the next figure. The shape points are displayed using the circles and the different colors correspond to the different segments. The continuous line represents the estimated trajectory for the road. Using the maps the road geometry can be extended to large distances, even in 300m or 400m as it is seen in the next figure.

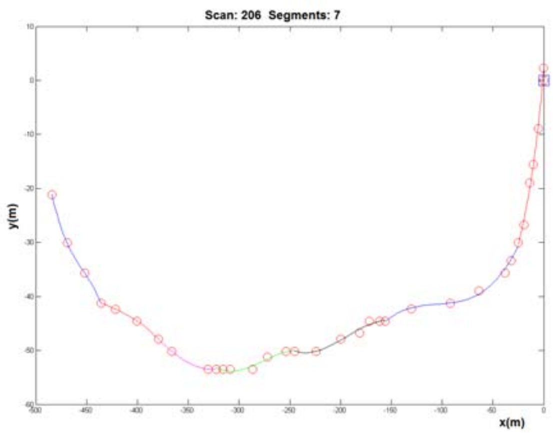

Fig. 2. Road geometry extracted using map data

In the following figure it can be seen the estimation of the road geometry using maps and how it can extend the predicted lane boundaries detected by the camera (red and green circles). The red circles in the middle of the lane are the shape points of the most likely path. The blue triangles are the Gps detections of the future position of the vehicle. It is seen that in sharp curves the map estimated borders increase the accuracy of the final output of the lane detection system.

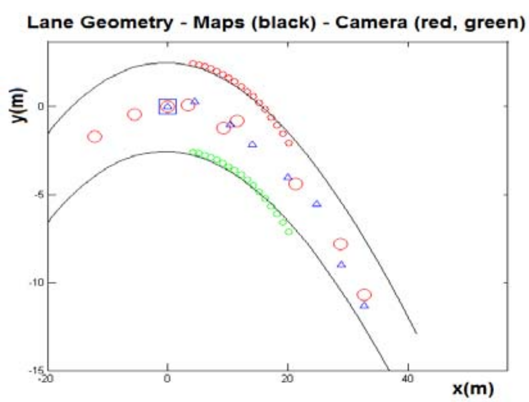

Fig. 3. Camera versus Map road geometry

An example of the lateral filter is shown in the next figure where it is shown a case of a camera failure. The failure is indicated with the transition of the blue line from 2 to 3. The green line is the estimated offset from the camera and the red line is the output of the lateral filter. It is seen that the system continues to provide the lateral offset of the vehicle from the middle of the lane for 2 seconds even if the camera fails to detect the lane markings of the road.

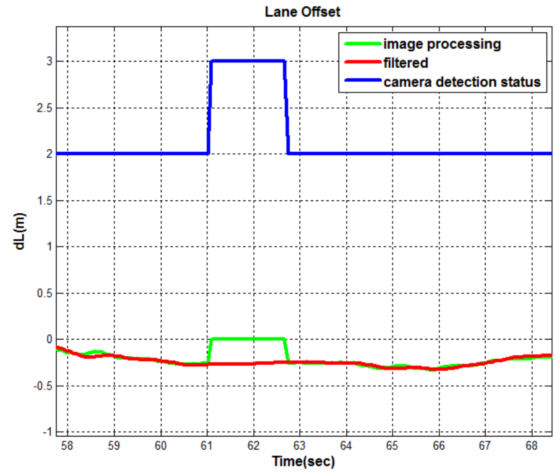

Fig. 4. Lateral Filter

In the next figure it is shown the estimated curvature using the lane data fusion algorithm. The blue line represents the image processing estimated values, the red represents the curvature estimated from the maps and the green represents the fused curvature.

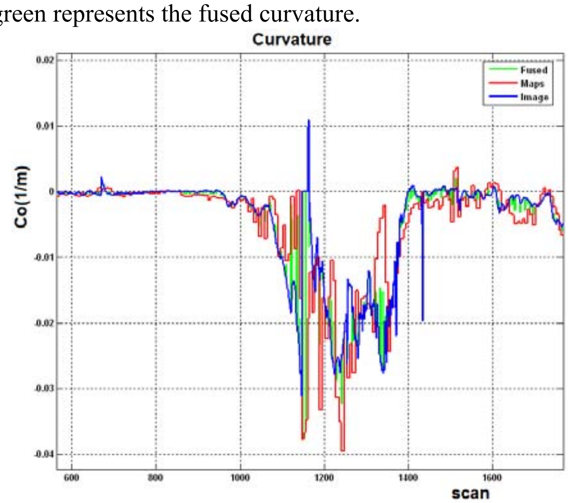

Fig. 5. Curvatures from camera and maps versus fused curvature

It is seen that the maps-estimated curvature has greater noise when compared to the one estimated using the camera detections. Also, the fused curvature is reducing the estimation error introduced by the two individual sources and provides a more realistic representation of the lane trajectory as it receives values between the two different levels of estimated curvature from camera and maps.

In the next table are shown some results after testing the algorithm in 4 different scenarios. More specifically the table is showing the length of the scenario in seconds, the percentage of failure of the individual lane geometry sources and the failure factor of the lane data fusion (LDF) proposed method. Failure is defined when the corresponding sensor fails to provide to the system information regarding the lane geometry or when the confidence associated with the provided information is below a certain threshold. In our case this threshold is defined to be 0.4. The percentage is extracted by dividing the total number of failures with the total number of scans.

TABLE 1
LANE GEOMETRY ESTIMATION SOURCES EFFICIENCY

Scenario	Length (sec)	Failure (%)		
		Camera	Maps	LDF
1	101	2.82	1.88	1.17
2	100	3.75	21.05	3.17
3	95	3.03	19.23	2.02
4	64	54.48	2.06	45.33

The lane data fusion algorithm is considered to be failing when the estimated confidence is below the value 0.4, or if the time threshold T_{LF} of the lateral filter of LDF module is expired. That is the reason why in the forth scenario the failure percentage of LDF is so big. The detection capabilities of the camera in the specific scenario are very limited due to environmental conditions (bad weather) and as a result there is a limited performance of the vision – lane detection system. Though, the final estimated lane geometry is improved due to the usage of the combined algorithm.

In the first scenario both sources have a very good performance and the fusion process further improves the final output. In second and third cases there are some scenarios where there is decreased performance from the maps lane geometry system. Though, the final output is very good due to the usage of the camera detected geometry.

V. CONCLUSION

Using map data it is feasible to extend the road geometry to greater distances in respect with existent sensors like radar and camera. It is also possible to increase the robustness of lane detection systems as it is now possible to continue to detect the lane geometry even if one of the active sensors of the vehicle fails to perceive the environment.

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