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A Situation-Adaptive Lane-Keeping Support System: Overview of the SAFELANE Approach

Angelos Amditis, *Member, IEEE*, Matthaios Bimpas, George Thomaidis, Manolis Tsogas, Mariana Netto, Saïd Mammam, Achim Beutner, Nikolaus Möhler, Tom Wirthgen, Stephan Zipser, Aria Etemad, Mauro Da Lio, *Associate Member, IEEE*, and Renzo Cicilloni

Abstract—Going beyond standard lane-departure-avoidance systems, this paper addresses the development of a system that is able to deal with a large set of different traffic situations. Its foundation lies on a thoroughly constituted environment detection through which a decision system is built. From the output of the decision module, the driver is warned or corrected through suited actuators that are coupled to control strategies. The input to the system comes from cameras, which are supplemented by active sensors (such as radar and laser scanners) and vehicle dynamic data, digital road maps, and precise vehicle-positioning data. In this paper, the presented system design is divided into three layers: the perception layer, which is responsible for the environment perception, and the decision and action layers, which are responsible for evaluating and executing actions, respectively.

Index Terms—Data fusion, integrated safety applications, lane-keeping support (LKS) system, lane tracking.

I. INTRODUCTION

ROAD-TRAFFIC accidents are caused by many different factors. According to an American study [1], a vast majority of all traffic accidents (96.2%) are caused by human error. Driver inattention is estimated to be involved in at least 25% of all police-reported crashes [2]. Within SAFELANE, accidents that are caused by driver inattention (e.g., drowsiness, fatigue, distraction) are of special interest since the developed system aims to prevent accidents resulting from poor lateral control.

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Lane-keeping-support (LKS) and lane-departure-warning (LDW) systems have been a subject of intensive research and development [3], [4]. Several systems are available on the market for several years. Since the precursor system that was introduced by Nissan in 2001, all the European car manufacturers propose such systems as first equipment. Even if these systems are primarily designed for comfort, they generally enhance safety by driver warning and active intervention in highway driving situations where needed actions are generally smooth [5].

Up to now, the most common techniques in lateral safety are based on lane trackers using monocular video sensors to detect the lanes up to 50 m ahead [6], [7]; in more recent publications, laser scanners [8], high-resolution radar [9], and infrared cameras [10] are also used [11], [12]. More efficient approaches propose fusion techniques to complement the yaw-rate-based road geometry, and estimate and predict changes in the curvature of the road ahead using a digital map and Global Positioning System (GPS) receivers, video cameras, and tracks from the radar or stationary obstacles that represent guardrails or posts [7], [13], [14].

While different warning channels are generally used, including haptic vibrations on the steering wheel and sided audio signals, active actions are generally delivered as an additive steering torque. It should also be noticed that some decoupled additive steering-angle solutions such as Advanced Front Steering systems are also available. Control techniques are of various types ranging from classical approaches to adaptive, robust, and fuzzy methods [15]–[17]. However, active systems that are able to handle various traffic scenarios and driving situations on the lane such as activation near the lane borders with the ability to steer back the vehicle center of the lane are still not available.

SAFELANE, together with LATERAL SAFE [18], comprises the lateral safety cluster of the Integrated Project–PREVENT dealing with lateral- and rear-area active safety applications. The research objective was to develop an LKS system to go beyond the currently available systems and to function safely and reliably in a wide range of even difficult road and driving conditions. The system should be usable in various types of vehicles, from passenger cars to heavy trucks, and be operable on motorways and rural roads. In addition to

passive LKS with haptic, acoustic, and optic human-machine interface (HMI) elements, this system was intended to actively steer back to the lane in critical situations.

In particular, the SAFELANE system has comprised an adaptive LKS application, which, in the event of a detected lane departure, triggers a driver warning or an active steering system. Most of the related work to SAFELANE in lane-detection systems is mainly based on vision sensors [19]–[21]. A model-based decision module processes the sensor data for situation awareness and deciding appropriate acting strategies, in particular, when the driver’s perception of the surrounding scenario is very difficult due to limited visibility, critical workload, or the driver’s inattention.

This paper is organized as follows: In Section II, the system concept and the architecture are briefly described, whereas in Section III, the design and the implementation of the main modules are provided. Section IV summarizes the main technological innovation, achievements, and proposals for future work in the relevant research field. Finally, Section V includes some conclusions.

II. SYSTEM ARCHITECTURE

The proposed system is structured on a model-based approach with the use of vehicle-side technologies. Its decomposition is made in three layers: the perception layer, the decision layer, and the action layer, which are detailed below (see Fig. 1).

The perception layer consists of a sensor system and image processing. The basic input comes from cameras that are monitoring the road in front of the vehicle. The cameras are supplemented by vehicle controller area network (CAN) bus data, digital road maps, and precise vehicle positioning (GPS). Radar provides supplementary information that is integrated in the data-fusion module.

The action layer comprises all system reactions in critical lane-departure situations and involves the control of acoustic or/and haptic warning actuators, as well as an active steering actuator.

The decision layer determines the current overall situation using a situation model with respect to the driver state, the actual driven maneuver, the environment, the lane, and the street condition. Based on the identified situation, the decision model determines the output to be sent to the actuator system. Input parameters are the most likely path (MLP) of the vehicle, the fused lane data, as well as the estimated future vehicle trajectory. Vehicle data like velocity, steering angle, and yaw rate are also integrated.

The situation model selects the most likely set of predefined situations, based on a set of information related to the vehicle, the lane properties, the street type, the estimated driver maneuver, the driver, and the environment around the vehicle. Following the method presented in [22], all the predefined situations are regarded as a combination of states of a state machine. Two of the situations considered in the situation model are briefly described below.

- Driver state: SAFELANE does not intend for a direct observation of the driver to determine the driver state;

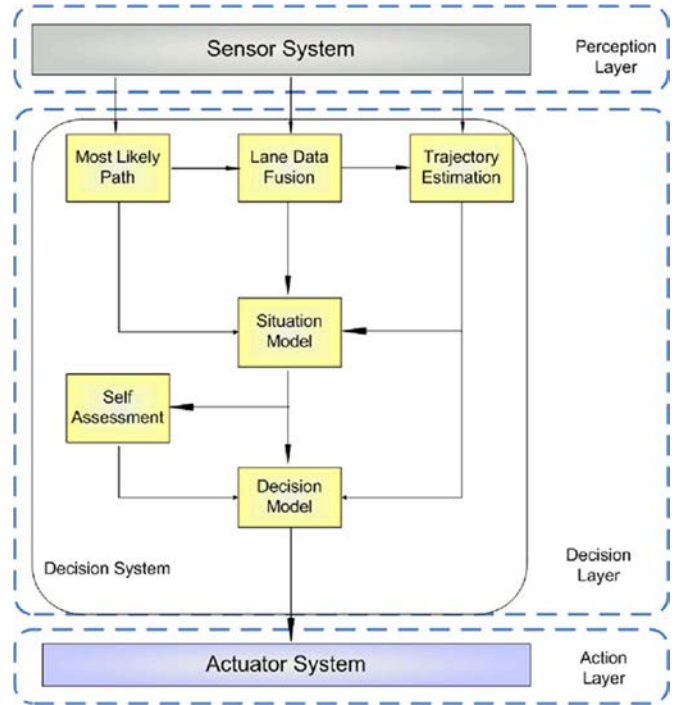


Fig. 1. Structure and modules of the SAFELANE system.

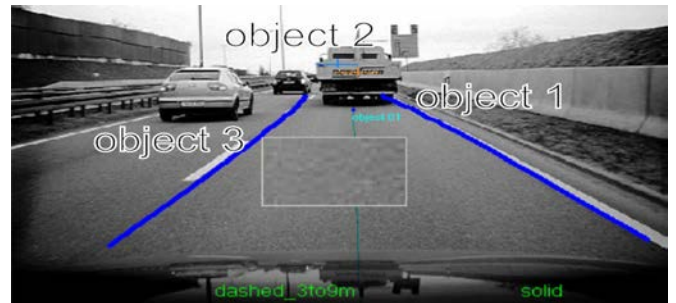


Fig. 2. Start of an overtaking.

for this estimation, we follow the approaches in [23] and [24] that are based on the variation of the vehicle lateral position analyzed with the low-frequency component of the power spectrum of the steering-angle signal.

- Maneuver estimation: An example on how an overtaking maneuver is represented in the state model is shown in Figs. 2 and 3.

In the first state or phase “overtaking possible,” the vehicle approaches an object (vehicle or obstacle; here, object 1) or follows a heading vehicle. Transitions T1 and T2 are described with a Sugeno fuzzy function. The inputs of the fuzzy function are given by ego velocity, distance, and relative velocity to the object. The second state “start overtaking” starts if the vehicle heads toward the overtaking lane. Transitions T3 and T4 represent, again, the Sugeno fuzzy functions analyzing the ego lateral position, the distance, and the direction of the tracked object. The third phase is the overtaking itself. The state model distinguishes between “overtaking in the same lane” (e.g., a bicycle) and the conventional “overtaking in the neighbor lane.”

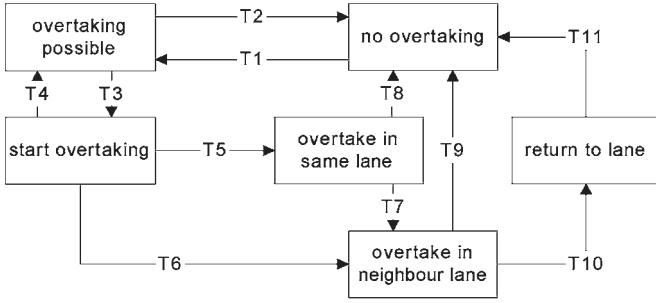


Fig. 3. State model of an overtaking maneuver.

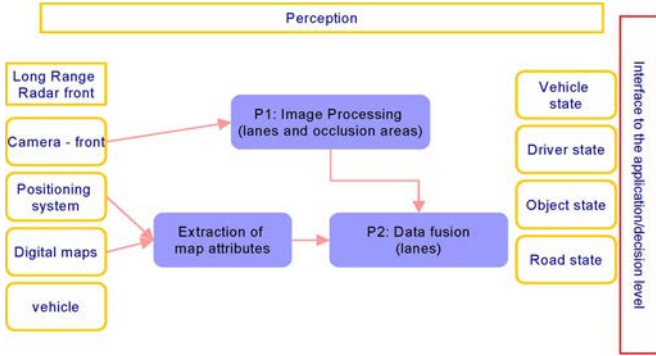


Fig. 4. Perception modules.

If a lane departure is predicted, the decision model decides, based on a fuzzy-like controller [25], whether this is intended. An intended lane departure activates the warning level “information.” If it is detected that the lane departure is not intended, the output is an acoustic or/and haptic warning, and the active steering will be enabled. The decision criteria are time to lane crossing (TLC), lane predicted minimum distance (LPMD), and time to lane predicted minimum distance (TLPMD), which will be analyzed in Section III-B.

III. DESIGN AND IMPLEMENTATION

A. Perception Modules

The perception modules are the following:

- image processing, which recognizes road and lane borders and estimates the geometrical parameters of an underlying lane model (e.g., clothoid), as well as the position and the orientation of the vehicle relative to the lane;
- lane data fusion (LDF), which treats data from different sources to furnish as output the tracking of the lane borders.

Fig. 4 highlights that the extraction of map attributes from the map database is included in the perception layer.

1) *Image-Processing Module*: The central component of the sensor system is the vision-based lane recognition, which detects the main and neighboring lanes (see Fig. 5).

The measurement points that are generated during the lane recognition process serve as input data to the lane-marking-type classification. The obstacle area detection marks regions in the image where other objects are located like a vehicle driving

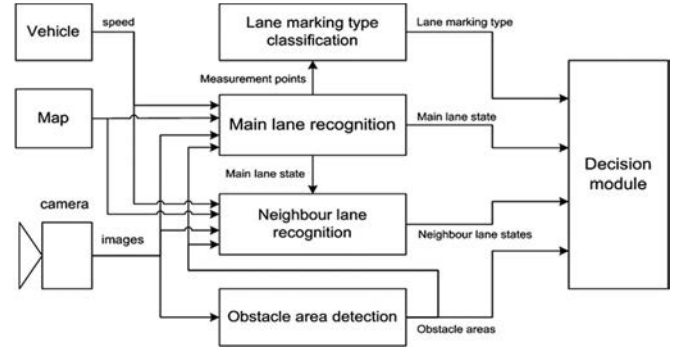


Fig. 5. Structure and interfaces of the image-processing module.

ahead. The lane recognition uses this information to restrict the search of measurement points to free road areas. For lane recognition, as well as for obstacle area detection, the vehicle speed is needed. Map data have been used to adapt certain lane-recognition algorithm parameters like the current lane curvature and width.

a) *Main lane recognition*: A model-based approach with the lane as a clothoid was chosen for the lane recognition because most streets and rail tracks are built according to clothoid geometry. The road surface is assumed to be flat, and, therefore, it could be modeled as a plane. The spatial vehicle state is described by its position and orientation relative to the lane.

In images that are taken from the camera, search areas are set, depending on the mode that the system is currently in. Measurement points are searched on lines in the image plane. At the program start or in case that the system “lost” the lane, no valid lane state is at hand—the system is in the initialization mode (see Fig. 6). Due to the fact that there are no available spatial hints about the lane ahead, the search area extends almost to the whole image on rigid wide lines (scan lines) in the initialization mode. If the lane recognition was successful in the previous image frame, a valid lane state exists and can be projected onto the image plane. Since the lane state frame-to-frame differences are usually small, it is reasonable to set the scan lines along the lane projection. In both modes, a list of scan lines serves as a basis to search for the lane contour edges in the measurement algorithm step. One edge per scan line most likely to belong to a lane border is selected out of the calculated edges. The selected edges are fed to the estimation stage where a new lane state is calculated.

—Search areas

In the initialization mode, the scan-line generation is quite simple and follows a rigid setting scheme. In the tracking mode, scan lines are set along the projected predicted lane state. A scan line is set perpendicular to the local lane border tangent (not necessarily horizontal) in world coordinates. The line width and the space to the next line are calculated, depending on the look-ahead distance. If the current lane border is classified as marked, the average lane-marking width is calculated and will be added to the scan line width. Projected in the image plane, the slope of the scan line is checked, and the scan line is rejected if a certain threshold is exceeded.

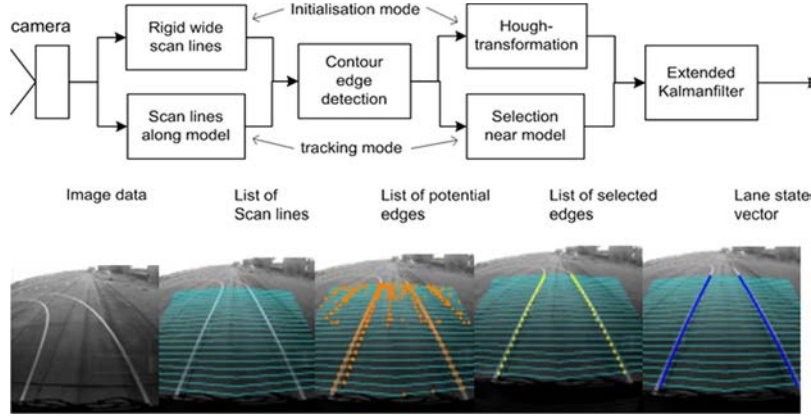


Fig. 6. Scheme of lane-marking detection and lane modeling.

—Measurement points

The Laplacian of Gaussian (LoG) operator is used for the gradient calculation as the basis for the edge detection. Edges are detected where the gradient magnitude is maximal in the gradient direction, a threshold is exceeded, and the gradient points into the local direction of the lane. At the detected edge pixels, the structure sensor [26] is computed. The quality of an edge pixel is computed by the ratio of its eigenvalues and the angle between the greater eigenvector and the tangent on the projected lane border. If the quality of an edge is good enough, a further validation is done by calculating little edge segments. Because the optical features (e.g., texture) are different with respect to the distance to the car, all measurement algorithm parameters like the gradient threshold are adapted according to the ratio of the pixel and the road plane coordinates.

—Selection

In the initialization mode, where no lane state prediction of a previous time step is available, an extended form of a Hough transform is employed. The operating modes of the Hough transform and the LoG are described in image-processing articles, e.g., [27] and [28]. Applied to the problem of lane measurement selection, the Hough transform equation is defined by the clothoid model, the vehicle position, and the direction parameters. During the tracking mode, the contour edge candidate next to the predicted lane state is used as a measurement point on a scan line.

b) Neighbor lane recognition: The information of the presence of neighbor lanes can be helpful in critical traffic conditions for lane keeping. Thus, the two directly neighbored lanes of the main lane where the vehicle is currently driving in are estimated as well. This is done with the same methods that are used for the main lane besides some deviations in the initialization mode. If the main lane recognition was successful, the neighbor lane recognition is triggered. The initial search areas of neighbor lanes can be set more precisely compared with the main lane because we know the location of one neighbor lane border, and usually, neighboring lanes have the same width. The neighbor lanes' pitch angle is assumed to be identical to that of the main lane (see Fig. 7).

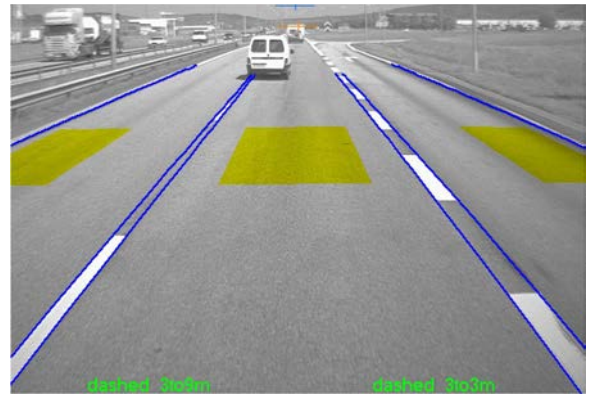


Fig. 7. Neighbor lane recognition; road texture check in yellow windows.

False detection can happen on structures that look like lane borders (e.g., crash barriers). Therefore, two additional tests are applied. The first one compares the road texture of the main lane and the neighbor lane. If the texture difference exceeds a threshold, the test fails. The second one checks if there are any obstacles inside the image area of the neighbor lane by means of the object mask image. If one of the tests is not successful, the neighbor lane recognition will be rejected.

c) Lane-marking classification: The knowledge of the road-marking types, which delimits the own lane, is of great importance for the lane-keeping task. Lane markings are assumed to be solid or dashed marker lines. Dashed lane markings have certain constant marking line width, line segment length, and line gap length. Therefore, these three marking characterizing values are taken as features for the marking-type classification. The needed information to determine the features is available in the lane border measurement points that are found in the course of lane recognition and can be fed to a classifier.

d) Detection of disturbing objects on the lane surface: The detection of lane markings in an image free of disturbing objects like other cars or side barriers, which may generate edges that can be misinterpreted as line-marking edges, is relatively straightforward and a typical demonstration example of image-processing tools. However, in many cases, disturbing objects are present; therefore, a greater algorithmic effort is required to exclude the “disturbed” image regions from the lane-marking detection procedure. One method to detect such

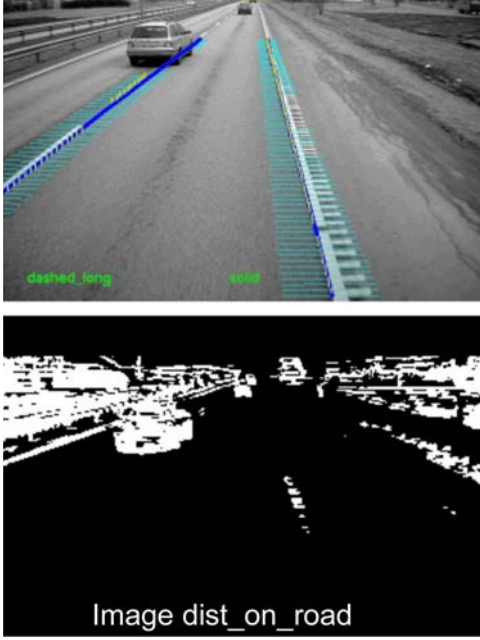


Fig. 8. Image and suppressed edge detection in the region of the car.

objects on a planar road surface is the analysis of motion-compensated difference images described in [29]. The idea behind is a motion compensation algorithm, which computes the required image-warping parameters from an estimate of the relative motion between the camera and the ground plane. Based on an optical flow approach, the algorithm estimates the warping parameters from displacements at corresponding image corners and image edges. The corresponding edges are calculated from an image and its successor (see Fig. 8).

e) Use of digital map data: Besides the use of map data for the lane-keeping decision module, the lane detection can also benefit from it. All lane-tracking systems have certain fixed configuration parameters. The determination of a configuration parameter is often a tradeoff between different scenarios concerning environmental and lighting conditions. The idea to enhance the performance of lane-detection systems with map data is based on the adaptation of certain configuration parameters with respect to information about the vehicle environment from a digital map.

2) LDF Module: All the previous systems will provide the fusion module with estimated values of the road, lane, and obstacle parameters and their respective values for the variance of the estimation error or/and a level of confidence. LDF provides a prediction even when lane markings are partially missing and, in some cases, when they are completely missing.

The role of this module is very important, as it leads to increased robustness of the overall system and extends the detected lanes by the camera sensor to greater distances using information from the positioning unit [26]. Cases where the camera fails to detect the lane markings due to restricted visibility or ambiguous markings can be handled using an appropriate filter that keeps estimating the offset and updates the rest of the parameters from the map data. Also, under normal conditions, the final estimation is refined, as the module combines the

camera data in lower distances with the map data in greater distances.

a) Data-fusion algorithm: The core of the algorithm for fusing the lane attributes is described as follows and in the following section.

- 1) If both the camera and map data are available, then the final output is a combination of these 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 linear Kalman filter for estimating the lateral state 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, which defines the capability of the filter to continuously provide lane-offset estimations without measurements, is usually set below 2 s. The state and the measurement vectors of this filter are the following:

$$X = [y_0 \ V_L \ A_L \ w]^T \quad (1)$$

$$Y = [y_0^{\text{cam}} \ w^{\text{cam}}]^T \quad (2)$$

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} and w^{cam} are the offset and the width provided by the camera, respectively. V_L and A_L are the lateral velocity and the acceleration of the vehicle (first and second derivatives of the offset), respectively. For the first three states, a constant acceleration (CA) model is used, whereas for the last state (width), a constant state model is used.

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

$$\begin{aligned} y_f &= w_c \cdot y_c + w_M \cdot y_M \quad x \leq d_C \\ y_f &= y_M \quad x > d_C \end{aligned} \quad (3)$$

where y_c , y_M , and y_f are the camera, map, and fused trajectories, respectively. d_C is the maximum distance of the camera trajectory. w_c and w_M are the weights for the camera and the map geometry, respectively, and are given by the following:

$$\begin{aligned} w_c &= \sigma_C / (\sigma_C + \sigma_M) \\ w_M &= \sigma_M / (\sigma_C + \sigma_M) \end{aligned} \quad (4)$$

where

$$\sigma_C = \frac{\sigma_C^2 - \sigma_{C,\min}^2}{\sigma_{C,\max}^2 - \sigma_{C,\min}^2} \cdot (x/d_C) \quad (5)$$

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 that is calculated for the first segment of the map data.

The main weight for the camera and the map data is based on the variance of the estimated values. When the variance increases, less confidence is assigned to the specific source of information. Also, the distance from the ego vehicle is considered. As the distance increases, 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 that are greater than 50 or 60 m. When there is no map or camera data, then the road geometry is given by the following:

$$y_f = y_{EV} \quad x \leq d_{EV}$$

$$y_f = \sum_{i=1, \dots, N_R} w_R^i y_R^i \quad x > d_{EV} \quad (6)$$

where y_{EV} is the lateral displacement, d_{EV} is a distance threshold, and N_R is the number of objects that are detected by the radar.

The curvature and the curvature rate in the case of the radar objects are 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:

$$C_0 = \omega/V \quad c_1 = 0 \quad (7)$$

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

$$w_R^i = \sigma_R^i / \sum_{j=1}^{N_R} \sigma_R^j. \quad (8)$$

B. Application Modules

The decision system is, to some extent, independent of the HMI and the actuator control, which is responsible for the lane-keeping function. It analyzes the current situation, identifies the risk and critical situations, and suggests the proper action, without knowledge of the HMI components.

1) *MLP*: Based on the information provided by the electronic horizon (EH) sensor and vehicle status data, the MLP module predicts the most probable route for the vehicle to take. Therefore, a minimum cost function for road classes in the digital map database combined with the vehicle's data leads the MLP to educated guessing of the most probable route. Depending on EH settings, two MLP types can be delivered:

- 1) MLP for a fixed distance (e.g., 900 m);
- 2) MLP for a defined time (e.g., 10 s), i.e., the extended length is calculated dynamically, depending on the current speed.

In the digital map database, available link attributes along the MLP (such as the "Number of Lanes") will be provided to other applications.

2) *TEM*: The trajectory estimation module (TEM) predicts the driver's intention in a short term by estimating the future path of the ego vehicle and its dynamics with respect to given tracked road geometry and infrastructure. The TEM is focused on the vehicle and the driver; it also calculates conventional and new parameters of typical LDW/lane-keeping systems like time to lane crossing or future lateral offsets.

The TEM has two subfunctions: On one hand, a dynamic vehicle model is applied that includes lateral and longitudinal vehicle properties; on the other hand, the estimated trajectory is compared with the actual lane geometry in the lane-change prediction function.

Moreover, the first subfunction assists the LDF function when lane information is missing from the lane tracker. Then, the only source of information is the map-extracted road geometry, which lacks lane position data (i.e., the position of the vehicle in the lane). The TEM subfunction acts as a dead-reckoning function for the digital map attributes.

a) *Dynamic trajectory estimation of vehicles*: To predict whether the vehicle is going to change lane in the nearest future, the trajectory that it is likely to follow must be known in that time period. This can be achieved using a first-order model such as the constant velocity model [30]–[32], which corresponds to a straight line. This simplified approach may introduce large errors in the prediction of the future path in the case that the ego vehicle is moving with CA. Thus, the CA model or the constant turn rate (CTR) model is the most suitable model for ego maneuvers. To correlate the two prevailing [33] types of motion, the CTR model and the constant tangential acceleration (CTRA) model, which was first introduced in [34] and takes into consideration both the yaw rate and the acceleration of the ego vehicle, can be applied. The road geometry is not used in the prediction of the vehicle's future path, making the lane trajectory and the vehicle trajectory uncorrelated.

The measurement space consists of the yaw rate and the velocity; first, a filtering process takes place to reduce the measurement noise. This is done using a Kalman filter with

- a state vector $[U \ A \ \varphi \ \omega]^T$, which consists of the velocity, acceleration representing the longitudinal motion, and the yaw angle/yaw rate representing the lateral vehicle dynamics, respectively;
- a measurement vector $[U \ \omega]^T$, which consists of the velocity and the yaw rate.

This way, the tangential acceleration of the vehicle is also available in the next step, which will be used to calculate the future path.

The prediction of the vehicle's trajectory is done in the ego-coordinate system (e.g., in the midpoint of the frontal bumper). The predicted trajectory is a matrix consisting of the future position of the vehicle for a fixed—a *priori* set—time period T_{max} . Each element of the matrix (x and y coordinates) corresponds to a specific "future time." The time step that is selected for the estimation of the future points is also fixed (e.g., 100 ms).

b) *Lane-change prediction*: The accurate knowledge of the lanes and the ego trajectory allows extending current methodologies that are used in LKS and LDW systems.

TLC is defined as the time duration that is available for the driver before any lane boundary crossing. Several research studies outlined the importance of this indicator for both driver performance evaluation and lane departure characterization [35], [36]. Among usual observations concerning TLC time evolution are small TLC value periods prior to lane departure. This happens particularly in the case of driver drowsiness, which generally leads to a slow rate of TLC decreases with the possible presence of one or several TLC local minima corresponding to driver corrections. On the contrary, in the case of vehicle loss control, the decrease of TLC toward zero is generally faster. Unfortunately, real-time computation of TLC is not easy due to several limitations to the availability of vehicle state variables, vehicle trajectory prediction, and lane geometry; however, computation time is also a limiting factor. Different TLC calculations are possible; they include simplifications that can be introduced, depending on the available sensors.

The static approach for the lane-change prediction is based on the estimation of the lateral velocity and the acceleration of the ego vehicle. Then, using a first- or second-order model, the time when the predicted lateral distance is getting equal to zero corresponds to the time that there is a lane change. To predict the lane change taking into consideration the lane geometry, a dynamic approach should be applied. The distances between the trajectories of the vehicle and the lanes are calculated. Thereby, the future lateral distance of the vehicle from the lane is extracted for a fixed time period. Thus, when this distance is getting equal to zero (or a minimum offset)—LPMD—it means that there is a lane change, and the time that is required for the ego vehicle to change the lane can be predicted (TLPMD).

The warning that indicates a lane departure will be created using the TLC parameter or the LPMD and TLPMD parameters.

A very simple model, as suggested in [33], takes into account only the lateral velocity of the ego vehicle, whereas it considers the lateral acceleration to be equal to zero.

For a more accurate estimation of the time when the vehicle crosses a lane, a second-order model can be applied. Thus, having the lateral distance of the vehicle, the lateral velocity, and the lateral acceleration, it is easy to estimate the time that is required for the vehicle to change the lane using a CA model. This, however, still leads to a static approach for finding lane changes, which does not take into account the lane geometry and the respective changes. It uses only the current lateral dynamic state of the ego vehicle, and it considers that, in the region where the vehicle is located, the road is nearly straight.

Alternatively, the LPMD and TLPMD parameters are used for a more realistic situation analysis, which takes into account not only the dynamic state of the vehicle but the curvature of the road as well. This method takes into consideration the predicted trajectory of the ego vehicle and the extended trajectory that describes the lane geometry to calculate the distances between the predicted points of the two trajectories. Then, having the distances with respect to time, the time when the distance is minimized is acquired, and then, if this distance is smaller than a threshold (or equal to zero), a warning is created, which indicates a possible lane change, and the time when this happens

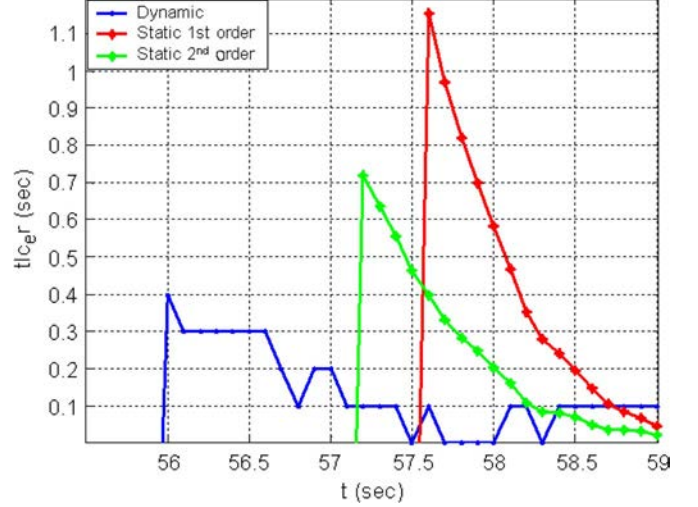


Fig. 9. TLC error calculation in a lane-change scenario (the benchmark of the conventional and proposed approaches).

is the TLPMD. The algorithm is presented in the following pseudocode:

$$\text{veh_traj} = \{x_V(i), y_V(i)\}$$

$$\text{lane_traj} = \{x_L(i), y_L(i)\}$$

$$y_L(i) = y_0 + \frac{1}{2} \cdot c_0 \cdot x_L^2(i) + \frac{1}{6} \cdot c_1 \cdot x_L^3(i)$$

$$x_L(i) = x_V(i)$$

$$\text{lat_off} = \text{veh_traj} - \text{lane_traj}$$

$$D(i) = y_L(i) - y_V(i), \quad i = 1, \dots, N$$

$$\text{LPMD} = \min \{D(i)\}$$

$$\text{TLPMD} = ii \cdot dt|_{D(ii)=\min\{D(i)\}}$$

if $((\text{LPMD} < \text{TH}_D)(\text{TLPMD} < \text{TH}_T)$

then warning = 1, else warning = 0 (9)

where N is the length of the future trajectory of the vehicle, dt is the time step that is applied in the calculation of the trajectory, and ii is the index of the point that corresponds to the minimum lateral offset between the ego vehicle and the extended lane.

The methods that were presented for predicting the time when the lane change is likely to happen are the first-order static method, the second-order static method, and the dynamic method using LPMD and TLPMD.

In the simulated test scenario, the vehicle is moving on a straight road and then enters a constant curvature bend where, after a while, it performs a lane change. The model that was used for the prediction of the vehicle's future path was the CTR and CA model (CTRA), and the length of the predicted trajectory was 40 points, with a time step of 100 ms (4 s). The lane change, in this case, is happening at time t equal to 59.4 s.

The error for the estimated time to lane crossing is shown in Fig. 9. The proposed approach in combination with the extended path prediction and lane fusion offers two

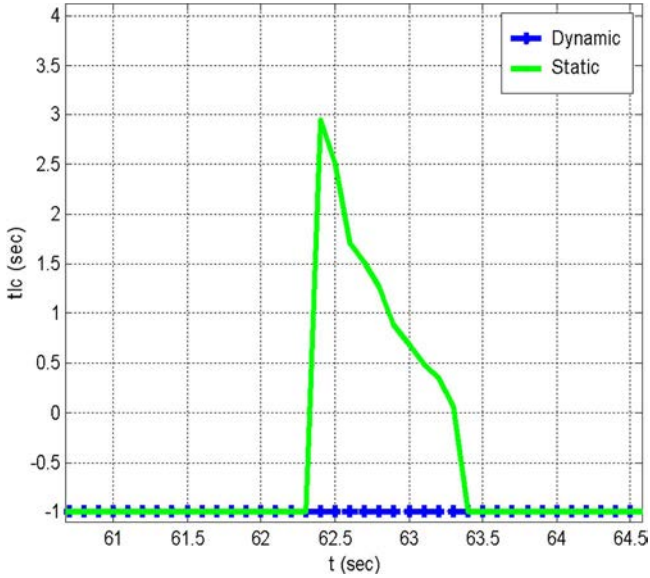


Fig. 10. Validation of a lane-drifting scenario.

advantages: On one hand, it predicts the lane change earlier than the static methods—3.6 s against 2.4 and 1.9 s for the two static TLC calculations, respectively, in the simulated scenario; on the other hand, it suppresses false alarms in some lane-drifting scenarios.

Finally, a lane-drifting scenario is presented, where the ego vehicle is maneuvering for 1–2 s in a straight road (i.e., lateral velocity not equal to zero) without changing lanes. In Fig. 10, TLC is calculated using the static and dynamic approaches. A lane-change warning is not produced using the dynamic approach, as it should be. Instead, the static model provides a false prediction for the lane change.

3) *Decision Module*: The decision system in the middle of the entire process of the SAFELANE architecture, in between the perception system and the actuator system, is responsible for the interpretation of the sensor data and choosing the appropriate action for lane keeping [37]. Its output is computed on the basis of the above-described perception and application modules. It then splits into six modules that interact by the use of specified interfaces, which are defined by internal data models:

- the MLP that estimates the vehicle route in the near future;
- the LDF fusing the lane data from different sensors to one lane model;
- the TEM that estimates the future trajectory of the vehicle in relation to the lane model;
- the decision module situation model: build a model of the current situation from the sensor data;
- self-assessment: estimate the reliability of the system;
- decision model: decide what kind of action should be taken from the current lane departure and situation.

The decision system takes the perception output, which contains estimations of states and attributes for the objects and entities that are situated on the same environment as the subject vehicle. The decision module aggregates the information from the perception module and applies specific models that

are compared with reference models of predefined situations. Additionally, the module infers fuzzy and binary relationships among the entities. Another important aspect of the module is the ability of self-assessment. The decision algorithms can estimate the confidence level of their output; therefore, all the modules that use the derived output are aware of the reliability of the information that is provided. This is reflected on the actuator module: If the reliability is high, active steering can be applied; otherwise, a warning (haptic or sound) is given to the driver.

Finally, the action is synthesized, transformed into the respective data format, and handed over as input data to the actuator system. The described transformation process is accompanied by a permanent self-assessment that decides how reliable and safe the decisions made by the system are.

C. Actuator and HMI Modules

The task of the actuator module is to execute the actions that are determined by the decision system. The actuator system manages driver warning and active steering. It receives the action request from the decision system in an adequate way. According to the requested action from the decision module, which is chosen on the basis of the current danger and self-assessment, more (or less) intrusive [38], [39] warning or intervening action requests are to be sent to the actuator. The actuator module processes this request information and provides the control signal to actual actuator and HMI means. To process this request information, action requests are translated by the actuator module in terms of steering-wheel angle/torque references that have been defined by suited algorithms in case of active steering. This includes control algorithms if intervening systems are to act and algorithms for the choice of the vibration waveforms if a haptic action has to be taken by the decision module [38]. The actuator system also performs self-assessment of the decision system actions and verifies the vehicle dynamic evolution. Safety-oriented actions have also been adopted. For being able to work in closed-loop operation, the actuator system uses information both from the decision system and vehicle sensors. The information is processed in a PC or, in the case of a smart actuator, in the actuator integrated hardware itself. Control loops are activated according to the decision system action request type. The actuator system also returns messages to the decision system informing it on assessment results and on the actual action realization.

1) *Actuator System Development*: The subsequent steps to correctly develop the actuator systems that have been implemented in SAFELANE demonstration vehicles have been defined and followed.

- We define data exchange between the actuator and the decision and sensor modules.
- Choice of the electric power steering (EPS): In this step, the type of EPS, taking into account how to integrate it in the vehicle, and whether the hydraulic power steering should be maintained, has been addressed. Studies about available space in the vehicle and the size of the EPS have been carried out as well. The determination of the sensors that are needed by the systems and whether redundancy

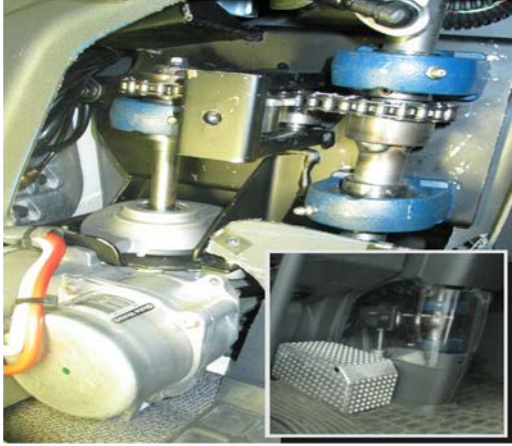


Fig. 11. EPS prototype integration in a Volvo (VTEC) demonstrator vehicle.

between sensors should be used were done. This step also addressed studies about how to include safety modules and self-assessment (see Fig. 11).

- Construction of the low-level actuator control: The construction of a system to drive the EPS to the correct angle and/or torque reference values has been carried out, including the necessary tests to assure the correct following by the actuator of the given angle/torque reference.
- We develop high-level control algorithms for active steering to calculate the steering torque/angle references to be sent to the EPS.

In the following, we concentrate on the last above-described step to give information that is related to the high-level development, active steering control, and HMI channels.

2) *HMI Development*: The use of the term human-machine cooperation (HMC) makes sense when a human and a machine are operating together in such a way that they can interfere positively by improving their individual performances or negatively by diverging their goals or a common goal. Many features of the HMC have been addressed in aviation, while research on this question is still to be developed in the car-driving domain, although automation is being rapidly introduced in the car, particularly for safety reasons (e.g., antilock braking system, electronic stability program). We specify the next three levels of interference processing between the driver and the machine [40]–[42] in terms of the different SAFELANE subsystems.

- 1) The action level concerns short-term actions; a minimal anticipation of the actions to be taken is involved.
- 2) The planning level concerns medium-term actions, with some planning involved by the driver.
- 3) Metacooperation level: Longer term actions are concerned here, as the planning by the driver of which road to take to get to his or her destination.

Based on these temporal frames, there are two main classes of assistance: preventive or foresighted driving and short-term decision assistance. This division suggests that the first one would concern mainly informative or warning tasks to help the driver and is related to the metacooperation level, whereas the second one could be based on warning and on active systems,

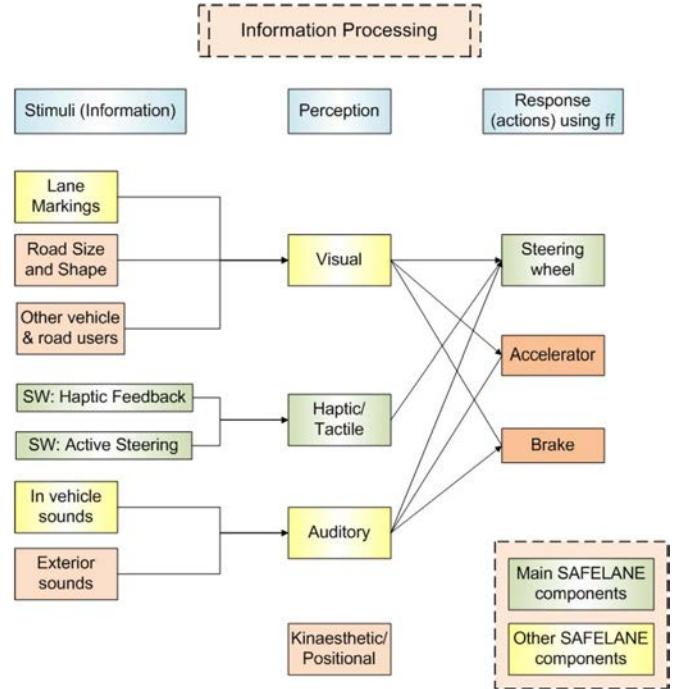


Fig. 12. Basic information, perception, and response flow for the SAFELANE HMI.

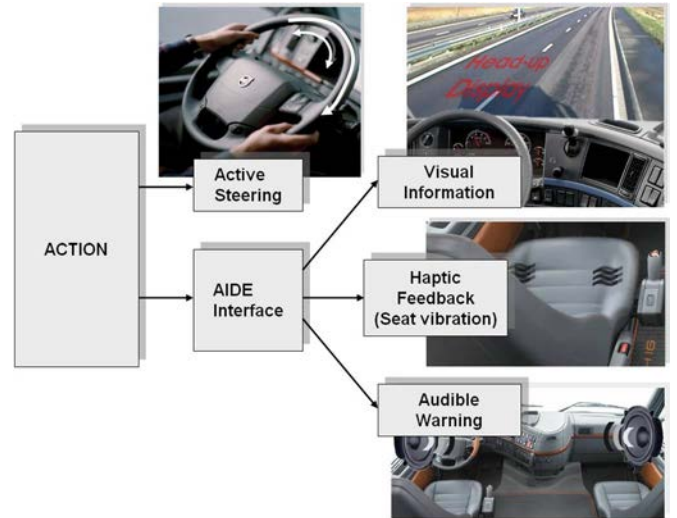


Fig. 13. HMI cooperation with AIDE.

like correction of the driver's action, and is related to planning and action levels. SAFELANE has addressed the latter where the proposed lane-keeping systems are declined according to cooperation modes. According to these modes, the system is progressively intervening in the vehicle control with respect to the driver [38], [41], [42]. Special classes of these possible cooperation modes are mainly of concern; mutual control modes, where a machine can criticize a driver's action (warning mode), suggest another action (action suggestion mode), prevent the driver from going too far (limit mode; e.g., prevent the driver to turn the wheels too much), or correct the driver's action (correction mode). Fig. 12 provides a view on the main HMI channels on which SAFELANE has acted.

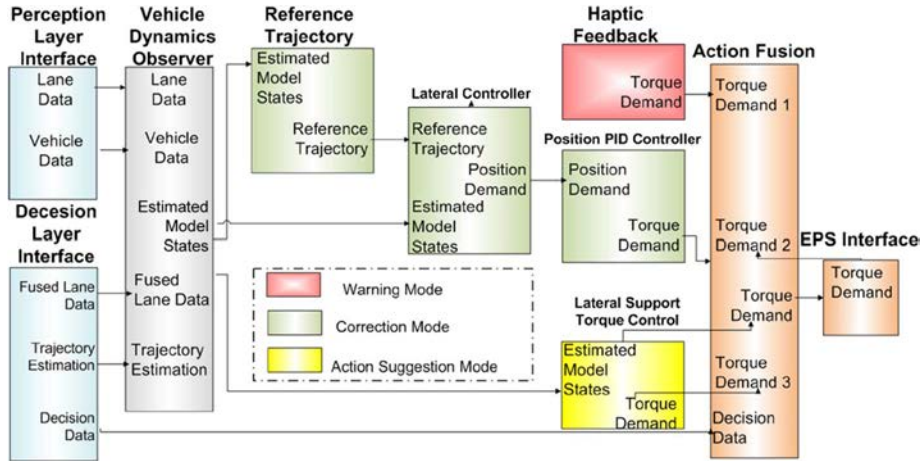


Fig. 14. Overview of the controller strategy.

During the project, a close and open cooperation with another European Union cofunded project named AIDE was established. SAFELANE and its functionality were used as the use case within the AIDE project. On the other side, SAFELANE has benefited from recommendations and cooperation on HMI devices [43], [44].

A driving simulator that is used for common development of AIDE and SAFELANE was equipped with a steering actuator for algorithm development and usability tests. An AIDE expert clinic evaluated the SAFELANE functionality and proved very positive with regard to the active steering functionality that was developed at that time. The overview of the concept that is used for the expert clinic is shown in Fig. 13.

In Section III-C3, we describe some of the results that have been built within SAFELANE for lane keeping by active steering.

3) *High Level Control for Active Steering:* As described above, to carry out lane keeping by active steering, the torque/angle reference to be sent to the EPS has to be calculated by a control algorithm. SAFELANE has proposed and implemented in its test vehicles a lateral control system that works with good performance even for very strong curvatures. If the vehicle drifts out of the lane, the proposed active system is turned on to help the driver to get back into the lane. The proposed system has important new features with respect to the known systems. While a look-ahead distance that is linear with the speed is a known performing solution, particularly in the highway context introduced in [36], the SAFELANE system makes use of a quadratic look-ahead distance of the speed, from which considerable improvement for active steering in tight curves could be attained. A strategy to optimize the use of the information coming from the lane-detection module is proposed, and the driver can deactivate the lateral control correction whenever he or she wants by simply manually counteracting the system with an automatic reactivation under a set of safety conditions. This control strategy is described in detail in [45].

In Fig. 14, an overview of the controller strategy as used and developed for the Volvo Technology (VTEC) driving simulator is given. The combination of three different modes is used: the warning mode, the action suggestion mode, and the correction

mode. The action fusion module decides, based on the current situation, the appropriate action to be performed at the steering actuator.

IV. DISCUSSION ON THE SCIENTIFIC OUTCOMES

A. Perception Layer

With regard to the perception layer and the sensor system, innovations are mainly related to the LDF approach that has provided the fusion of the vision sensor information with radar object trails and the digital map data information. The test results have shown that the environment perception system is able to solve complex situations, e.g., roundabout approaching, which were indicated as critical scenarios from previous research projects. Another example of enhanced behavior of the lane-sensor fusion is the capability to also reconstruct lane geometry when lane markers are not present (for a short period) or occluded.

B. Application Level

All sensors provide their information to the decision system, which includes a sensor fusion of vision sensor information, vehicle sensor information, map data, and MLP information, as well as radar sensor information. This sensor fusion enables an enhanced environment perception compared with simple vision-based lane-tracking systems.

An important innovative aspect in SAFELANE is the MLP module and the usage of digital map data with enhanced Advanced Driver Assistance Systems (ADAS) attributes. This information extends the limited range of onboard physical sensors such as radar or cameras.

Future vehicle subsystems dealing with safety, comfort, and intelligent navigation require accurate map data from the EH. The latter provides all probable paths ahead of the current position of the vehicle along with any data available through the map data provider and other in-vehicle systems. The EH that accompanies the positioning unit is not just a conventional sensor but rather a virtual sensor providing information retrieved from a digital map database (see Fig. 15).

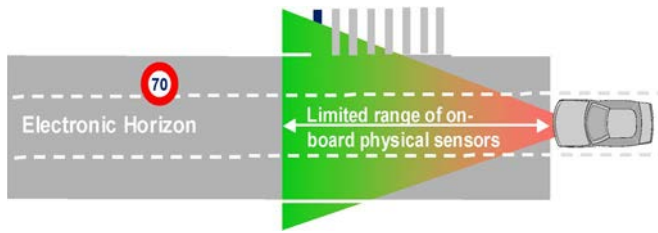


Fig. 15. Extension of physical sensors with the EH.

Based on the information provided by the EH sensor and vehicle data, the MLP algorithm predicts the most probable route for the vehicle to follow. Therefore, a minimum cost function for road classes in the digital map database combined with the vehicle's data leads the algorithm to educated guessing of the most probable route. Using the enhanced ADAS attributes and environment parameters provided by the EH along the MLP (i.e., the number of lanes, the lane width, the lane-marking type, and the curvature), the environment perception can be improved by removing ambiguities in the lane detection and, thus, increasing the availability and the reliability of the system.

V. CONCLUSION

SAFELANE has developed a safety system for avoiding lane departures for a large and complex set of traffic scenarios. Because of the modular nature of the SAFELANE system, it is easy to introduce parts of the results into products. In a short-term perspective, these results will be used to enhance current state-of-the-art LDW systems. Looking a little bit further ahead, the introduction of active steering will lead to vehicles with complete LKS systems on the market.

Furthermore, other driver assistance applications such as lateral cruise control and collision avoidance by steering share many of the technological challenges of LKS. Future research and product development projects focusing on these kinds of applications will certainly benefit from the experiences that are gained throughout the SAFELANE project.

Outputs from the perception layer coupled to robust control strategies and a suited HMI have permitted to develop a system that is able to give the driver a warning or a corrective action in case of unintentional drifting out of the lane. In particular, based on information coming from the sensing system and on a model-based adaptive decision component, it has been possible to provide an assistance system for the driver to keep in the lane. Starting from a model-based approach, it is possible to determine the trajectory of the vehicle and recognize if it is in a straight road or if it is approaching a bend. This fact implies to have a function that is always adapted to the driving situation and to be configured to different sensors or actuators. These objectives have been met by developing a common decision system that was integrated into the demonstrator vehicles. With respect to the traditional LDW systems, this adaptiveness and flexibility of the developed system represents a relevant improvement on the performance of the system.

In the action layer, several HMI aspects have been evaluated with regard to user needs and user acceptance. Specific results will shortly be presented in a follow-up paper from the SAFELANE working team.

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