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INTEGRATION OF CAR-2-CAR COMMUNICATION AS A VIRTUAL SENSOR IN AUTOMOTIVE SENSOR FUSION FOR ADVANCED DRIVER ASSISTANCE SYSTEMS

[1]Röckl, Matthias*, [2]Gačnik, Jan, [2]Schomerus, Jan
[1]DLR (German Aerospace Center), Institute of Communications and Navigation, Germany
[2]DLR (German Aerospace Center), Institute of Transportation Systems, Germany

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ABSTRACT – Advanced driver assistance systems (ADAS) require a comprehensive and accurate situation model. Often in-vehicle sensors do not provide sufficient quality and quantity of information to fulfill the demanding requirements. Car-2-Car communication can be seen as an adaptive sensor that provides additional information regularly but also on demand. Due to the fact that Car-2-Car communication strongly depends on the penetration rate, we argue for a seamless integration of Car-2-Car communication as an additional sensor in automotive sensor fusion. With increasing penetration rate the sensor fusion will significantly benefit and eventually unfold its full potential. Due to the fundamentally different measuring principles of in-vehicle sensors and information provided by Car-2-Car communication, redundancy and complementarity can be leveraged to a great extent, thus, increasing accuracy, reliability and robustness of the situation assessment.
In addition to a detailed description of the fusion algorithm this paper outlines DLR's system architecture for ADAS and an enhanced ACC as an application example to show the potential of our approach.

INTRODUCTION

Being a *development member* of Car-2-Car Communication Consortium, the *German Aerospace Center* (DLR) takes part in the quickly evolving standardization process of Car-2-Car communication technology. As already described in (1) this technology offers a wide range of support for improvement of existing applications and enables new applications in the field of *Intelligent Transportation Systems* (ITS). Great potential for Car-2-Car communication is seen in driver assistance systems. The focus of the use cases described by the Car-2-Car Communication Consortium is on supplying information and warnings to the driver, for example cooperative collision warning, traffic jam warning, decentralized floating car information.

A lot of these applications rely on cooperative awareness, creating the demand for a certain rate of market penetration (5% for traffic information propagation, 10% for inter-vehicle danger warnings) (1). In economics, this effect is called network externalities (2), indicating that an individual user benefits from a technology only when a certain amount of others use this technology, too. One possible enabler for the first customers of Car-2-Car communication technology might be deployment of infrastructure or Internet based services, since these do not rely on a high penetration rate of Car-2-Car communication.

From the drivers point of view, the scenarios illustrated by the Car-2-Car Communication Consortium primarily address guidance tasks, and even non-driving related tasks. Driver assistance systems focus on the interaction modes *information* and *warning*. Thinking beyond the initial market penetration of Car-2-Car communication technology, the use of this technology becomes more valuable for safety-critical applications with every unit sold.

The use case and the respective technology described in the scope of this paper deals with the use of Car-2-Car communication in active driver assistance in the driving-related layers *maneuver* and *stabilization* but could also be extended to the *navigation* layer. The focus is on the generic integration of Car-2-Car communication technology into a vehicle's system architecture. Therefore, it is treated as a virtual scalable sensor, being used in a sensor fusion with in-vehicle sensors. Through this abstraction the additional information may be incorporated into situation awareness of driver assistance systems without making them directly rely on the availability of a wireless link.

The remainder of the paper is structured as follows. Section 2 gives an overview of the system architecture and shows how Car-2-Car communication can be integrated as a virtual sensor. One of the essential components of the system architecture namely the sensor fusion is described in detail in section 3. Section 4 introduces *Cooperative Adaptive Cruise Control (CACC)* as a potential application that significantly benefits from additional information provided by Car-2-Car communication. The paper ends with a conclusion given in section 5.

SYSTEM ARCHITECTURE

Regarding the development of driver assistance systems DLR's system architecture concept (3) strongly encourages human-centered development process and design. A service-oriented paradigm is used for software development and domain modeling following the three layer model of human driving operation, as illustrated in table 1.

Behavior	**Assistance**
Knowledge-based	Navigation
Rule-based	Maneuver
Skill-based	Stabilization

Table 1: Three levels of control for human action.

Such a system design helps matching the mental model of a function (the driver's expectation of a system's behavior) with the functional behavior itself (*understandability*). The way to achieve this goal is being outlined by two methods. Either the driver may learn to use a technical system (adaption of human behavior) or the machine may be designed to match the human expectations as best as possible. In the latter case (adaption of machine behavior) the possibilities are further enhanced by a technology that is able to fit the driver individually.

A great step towards customization (personalization) of assistance functions on the technological side is the use of Car-2-Car communication. Additionally to the information that will be distributed by every vehicle regularly (i.e. position, velocity, etc.) using periodic beaconing, the Car-2-Car communication can be used to retrieve information on demand (use a certain *service*) aiming at optimizing the individual use for the driver.

This additional information may be orthogonal to information delivered by in-vehicle sensors and might therefore be used to broaden situation awareness. On the other hand, redundant information may be used to verify assumptions generated by in-vehicle sensor measurements and increase robustness in case of in-vehicle sensor failures.

Since the quality of in-vehicle sensors and wireless communication is dynamically changing, it is necessary to be able to prioritize information demands for the Car-2-Car communication module. This prioritization depends on the demand of driver assistance systems and the current quality of in-vehicle sensors. To be able to fulfill non-functional requirements like maintainability and portability we propose the following scheme:

- Each of n driver assistance systems ADAS_i has certain demand $d_i(\cdot)$ for certain information. This demand $d_i(\cdot)$ is being passed to a situation analysis module. In return, it receives a certain quality of information $q_i(\cdot)$.
- The situation analysis module prioritizes parts of its environment model using demands $D_j(\cdot)$.
- The sensor fusion module (CODAR – Cooperative Object Detection And Ranging) knows specifics about the vehicle configuration, including online sensor quality and Car-2-Car connectivity. Using the prioritized demands $D_j(\cdot)$ it dynamically allocates and optimizes the use of the available wireless resources, delivering information quality $Q_j(\cdot)$.

The overall architecture overview is illustrated in figure 1.

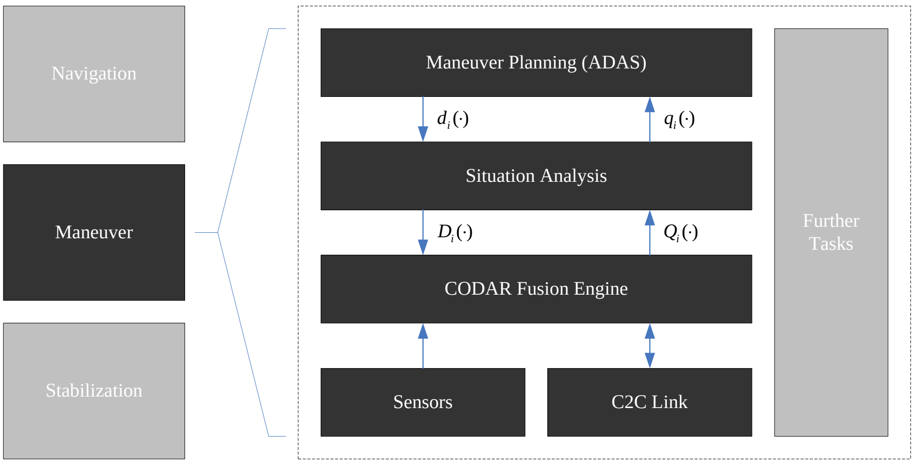


Figure 1: Functional architecture involving Car-2-Car Communication

SENSOR FUSION

By integrating this new sensor module in the vehicle system architecture additional information becomes available. This information might be complementary or redundant to the information provided by in-vehicle sensors, thus, increasing robustness, reliability and accuracy of the situation assessment can be gained.

In order to realize these advantages, the information given by different sensors has to be joined together. This has to be done in a flexible, self-adapting way due to the inherent uncertainty in the sensor measurements facing varying application requirements. Uncertainty in sensor measurements occur due to:

- inherent sensor noise (inducing inaccuracy of measurements)
- sensor failures and malfunctioning (resulting in loss and discontinuation of measurements)
- physical limitations of sensor technology (resulting in incorrect, incomplete or inaccurate measurements)

The virtual *Car-2-Car* sensor additionally is subject to:

- unreliability of wireless message distribution
- delay of data processing and medium access
- malicious intruders trying to manipulate the system

A fusion algorithm that joins locally generated measurements with information provided by other vehicles via Car-2-Car communication has to cope with all these peculiarities accordingly. For this purpose the fusion algorithm has to exploit causal relations of the measurements emerging as a result of their redundancy and complementarity. Furthermore, the recurrence of sensor measurements, e.g. periodic radar measurements or Car-2-Car beaconing, has to be incorporated and exploited appropriately. Therefore, we decided to use particle filtering for the sensor fusion and dynamic state estimation. The outstanding criteria is in the ability of the particle filter to traceably process multiple hypotheses given recurring noisy and unreliable sensor measurements, nevertheless, still providing controllable computation complexity.

The key idea of particle filtering is to represent the posterior distribution of the state estimation by a set of discrete samples, so called *particles*. Particle filters use sequential Monte Carlo methods for Bayesian inference to predict and update the estimated state on the occurrence of observations. This allows to carry along several hypotheses each assigned with a respective weight providing a fast and accurate adaptation to sensor noise and incomplete measurements, even with complex sensor and state transition models (4).

Similar to other Bayesian filter techniques, such as the well-known kalman filter and its extensions, the fundamental core of a particle filter is based on *predication* and *update* which repeats recursively. Thus, according to Chen (5) Bayesian filtering can be seen as a recursive *prediction-correction process* based on the following formulas (see also fig. 2).

Prediction:

$$p(\mathrm{x}^k|\mathrm{z}^{1:k-1}) = \int p(\mathrm{x}^k|\mathrm{x}^{k-1})p(\mathrm{x}^{k-1}|\mathrm{z}^{1:k-1})d\mathrm{x}^{k-1} \tag{1}$$

x^k	state space at time step k
z^k	measurements at time step k
$\mathrm{z}^{1:k}$	$= \{z^i, i = 1, \dots, k\}$

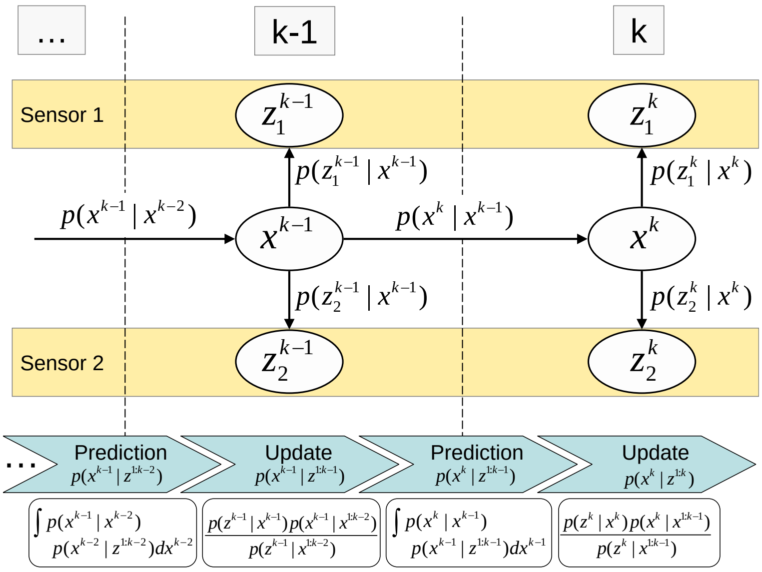


Figure 2: Prediction and Update for Bayesian filtering given observations of two sensors

Update:

$$p(\mathrm{x}^k|\mathrm{z}^{1:k}) = \frac{p(\mathrm{z}^k|\mathrm{x}^k)p(\mathrm{x}^k|\mathrm{z}^{1:k-1})}{p(\mathrm{z}^k|\mathrm{z}^{1:k-1})} \tag{2}$$

In case of several sensors the measurement z can be seen as a set of measurements $\{\mathrm{z}_1, \ldots, \mathrm{z}_m\}$ with z_j generated by sensor $\mathrm{j} \in \{1, \ldots, m\}$ whereas again each sensor measurement z_j can be composed of several cohesive measurements $\mathrm{z}_{j,1}, \ldots, \mathrm{z}_{j,d}$ (e.g. latitudinal position `lat`, longitudinal position `lon`, plus the respective accuracies `lat_acc` and `lon_acc`).

The state space x which can be composed of several state variables $\{x_1, \ldots, x_T\}$ includes all *variables of interest* that are required to fulfill the respective application demands. The variables of interest do not have to be sensed individually by a sensor but may also be inferred from other variables of interest based on their causal relation (by predictive and diagnostic reasoning). For the dynamic state estimation the transition of the state space from its Markovian parents is based on a respective transition model. E.g. a microscopic car-following movement model, such as the Krauss model (6) can be used as the basis for vehicle tracking.

The likelihood $p(\mathrm{z}|\mathrm{x})$ of a sensor measurement z given a certain state x encodes the measurement noises, unreliability and trustworthiness. Hence, this likelihood has to be chosen with special diligence. The likelihood function represents a core component for multi-modal fusion of in-vehicle sensors and the virtual Car-2-Car sensor, and determines success or failure of the whole system. It has to take into account qualitative aspects related to the measurement noise and quantitative aspects resulting from false positives (i.e. false detections) and false negatives (i.e. undetections) emerging from the above mentioned measurement errors. Furthermore partial redundancy, e.g. due to partial overlapping detection zones, has to be addressed in the likelihood function.

Thus, appropriately configured particle filtering provides a flexible and versatile solution for dynamic state estimation incorporating multiple sensors with inaccurate and unreliable measurements. An implementation of an ADAS utilizing Car-2-Car communication as additional sensor is provided in the following section.

COOPERATIVE ACC

The adaptive cruise control (ACC) system is well-known and standardized (7). Additionally to a cruise control system, it governs the distance or time-gap to the preceding vehicle. It uses an environment sensor, like radar or lidar technology to detect and range the preceding vehicle.

The conventional ACC system has been reorchestrated from several base services, which have been designed according to the three layer model (see figure 3). For seamless deployment DLR’s service-oriented architecture framework DOMINION is used. Specialized code for integration in different runtime environments (RTE) is generated from the formal service descriptions (8).

The major elements in the *stabilization* and *maneuver* layers of an ACC system can be described as follows.

- *CODAR Fusion Engine* – This component creates an image of the local surrounding. In our case this at least involves an environment sensor (radar, lidar) and Car-2-Car communication providing at least position data, e.g. determined by the Global Navigation Satellite System (GNSS).
- *Situation Analysis* – Analysis of the local environment around the vehicle, for the ACC operation the area in front of the ego vehicle is most important.
- *Maneuver Planning* – After the analysis of the situation in the local environment, a trajectory is being planned. In the case of an ACC system, this means planning of approach behavior towards the preceding vehicle.
- *Maneuver Execution* – The trajectory is being executed by the available actuators. In this case the actuators for longitudinal control (throttle, brake) are used.

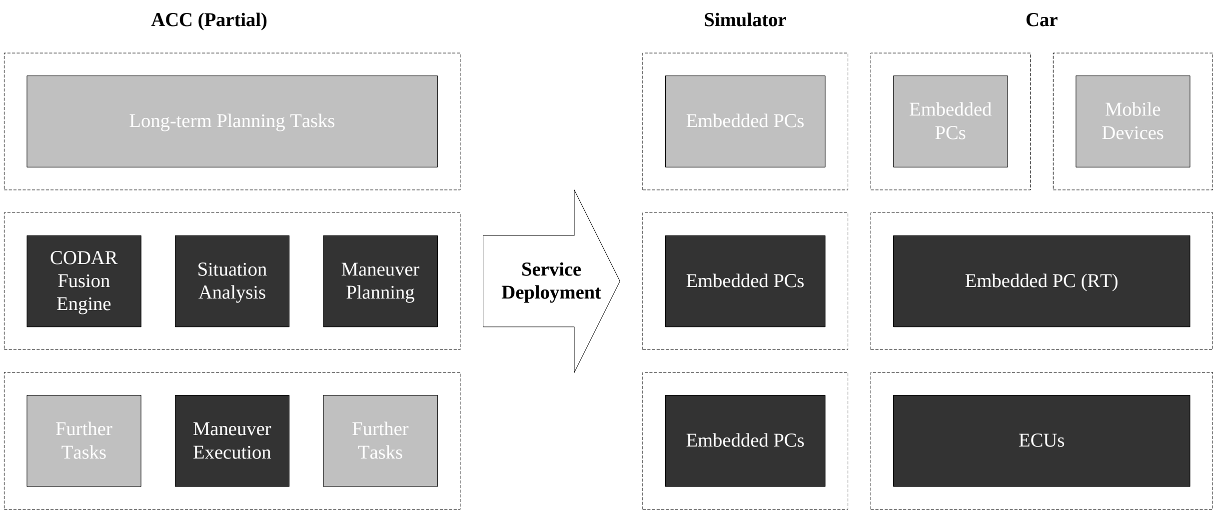


Figure 3: Deployment of the ACC services towards different research facilities

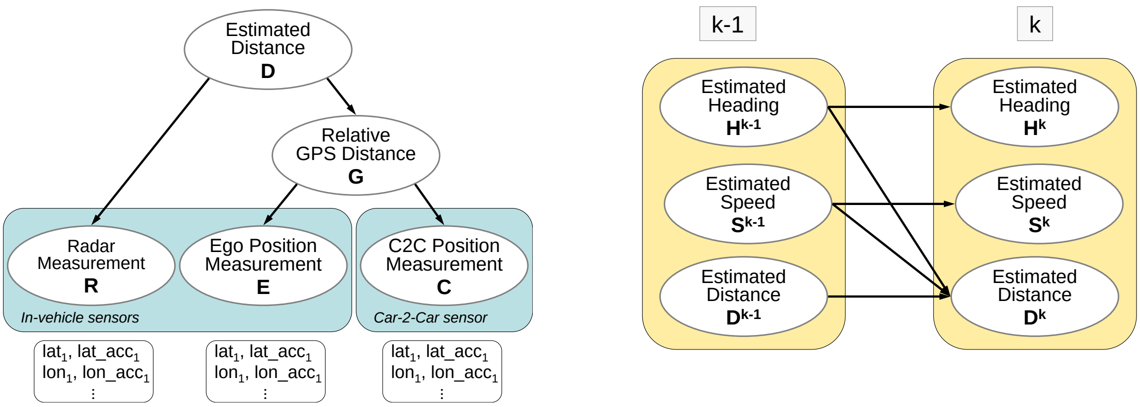
Through the use of Car-2-Car communication, sensor specific problems (e.g. detection of lateral distance using radar technology) and general drawbacks of current in-vehicle sensors are being addressed:

- *Limited field of view* – The field of view of a radar system, especially the detection angle is limited. This hinders the continuous distance estimation to the preceding vehicle in scenarios with narrow curvatures or hilly courses.

- *Poor foresight* – Furthermore, detection and ranging systems such as radar, lidar or camera are not capable of detecting objects located behind their reflection points. Thus, it lacks lookahead functionality, meaning that there is no way to detect what the vehicle in front of the preceding vehicle is doing, which of course influences the behavior of the preceding vehicle. Knowledge of this would improve the control strategy for approaching and following a vehicle.

- *No maneuver recognition* – Radar, lidar or camera sensors merely measure the effect of maneuver, e.g. the decreasing distance, if the preceding vehicle brakes. This delays the reaction time of the control strategy. If instead the causes, i.e. the initiation of a braking maneuver is made available to the ego vehicle via Car-2-Car communication, this boosts the use of cooperative ACC in dense traffic situations.

- *Restricted identification* – Radar, lidar or camera sensors are normally not capable of directly identifying vehicles. Thus, measurements can not easily be assigned to individual vehicles, and measurements caused by several vehicles can in certain constellations not be separated directly, e.g. due to a limited angular resolution of radar (9).



(a) Static Fusion Model for CACC

(b) Dynamic Fusion Model for CACC

Figure 4: Fusion Model

Information additionally provided via Car-2-Car communication can supplement the information gathered from in-vehicle sensors filling the above mentioned gaps and increase the accuracy and robustness of the system. The main focus of this paper lies in the provisioning of position related information in order to extend the field of view and enable a better foresight.

Therefore the estimated distance to a relevant vehicle is determined by two variables of interest namely the *Radar Measurement R* and the *Relative GPS Distance G* which is determined by the *Ego Position Measurement E* and the *C2C Position Measurement C*. Figure 4(a) shows the static fusion model with the random variables *D, G, R, E, C* and their causal relations as directed arcs. Evidence is provided to the variables *R* and *E* from the in-vehicle sensor system. Evidence to variable *C* is provided by the Car-2-Car sensor system. The *Relative GPS Distance G* and the *Radar Measurement R* share redundant information due to overlapping detection zones, thus increasing accuracy and robustness for detection and ranging. Additionally, the *Relative GPS Distance G* complements the *Radar Measurement R* in the relevant detection zone which is not covered by *Radar Measurement R* due to its physical limitations.

In order to exploit temporal causal relations between recurring measurements in dynamic traffic environments, the distance estimation is created as a time-sliced prediction-correction process. A particle filter with 1000 particles as described in the previous section is used for the dynamic state estimation and sensor fusion. The respective dynamic fusion model is depicted in figure 4(b).

In order to fulfill all requirements specified by the set of driver assistance systems $\{ADAS_i, i = 1, \ldots, n\}$ the fusion engine dynamically adapts its structure and evidential instantiations. Thus, the fusion engine adapts to the most demanding requirement given the set of demands $\{d_i(I), i = 1, \ldots, n\}$ for a variable of interest I which is imposed by the set of ADAS. The adaptation has to be performed in accordance with the evidence already given. For the CACC this means that in cases where the state estimation based on available sensor measurements already fulfills the given requirements no other evidence has to be incorporated. But in cases where the requirements are not fulfilled additional evidence provided by the Car-2-Car sensor system (e.g. high accuracy position information, heading, speed, etc. of the target vehicle) will be exploited. Therefore this information will be prioritized on the wireless channel accordingly because of its increased importance for the problem solving.

Figure 5 presents a screenshot of our initial simulations showing the cooperative situation assessment of the ego vehicle. The figure shows an increased availability of the position estimation which extends the limited field of view of the radar sensor. In overlapping detection zones, i.e. the unobstructed field of view of the radar sensor, a higher accuracy of the position estimation for vehicle *A*,*E*,*G* (*F* is obstructed by *A*) is given. This can be seen by a denser distribution of particles for the vehicles within this area. The vehicles *B*,*C*,*F*,*H* which are not detected by radar but are located in the coverage area of Car-2-Car communication show less accurate position estimations due to lower accuracy of GNSS positioning and no redundant measurements of the radar sensor. But still the mean of the particle distribution shows a quite exact match with the real vehicle position. Thus a sudden lane change of vehicle *B*, *E* or even *G* causing the preceding vehicle *A* to brake hard can be detected in time. This enables a much better foresight for CACC.

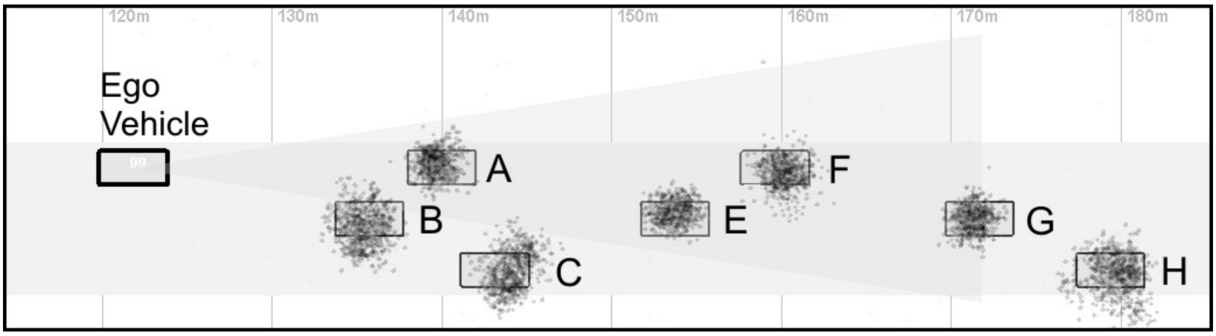


Figure 5: Cooperative situation assessment for Cooperative ACC

CONCLUSION

Summarizing, this paper presented the integration of Car-2-Car communication for sensor fusion in future advanced driver assistance systems. These systems will adaptively exploit information given by in-vehicle sensors as well as other vehicles or roadside units in their vicinity. In order to join the heterogeneous information and provide a sophisticated estimation of the current situation we proposed to use particle filtering for the dynamic state estimation and multi-sensor fusion. This fusion engine will be a key component of our service-oriented system architecture.

To show the applicability of our approach we introduced an enhancement of ACC, namely Cooperative ACC, which integrates position information provided by the vehicles in the vicinity via Car-2-Car communication additionally to radar or lidar sensor measurements. The result was a high-precision image of the current driving situation which allows a fast and accurate situation assessment and thus increases safety, efficiency and comfort of future driving.

Next steps will be the integration of our approach into our test vehicles in order to perform real test runs and evaluate the concepts under realistic conditions.

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