Sensing the environment for future driver assistance combining autonomous and cooperative appliances

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Abstract

Current driver assistance systems such as Adaptive Cruise Control (ACC) and in particular future assistance systems (e.g. Collision Warning) anticipate high demands for effectiveness and accuracy of detection and ranging methods for vehicles within their vicinity. Autonomous systems such as radar which are already integrated into a multitude of vehicles meet these requirements to only a limited extent. As an alternative, cooperative systems for detection and ranging will be enabled by future Vehicle-2-Vehicle communication. But even if the technology is deployed in every vehicle, cooperative detection and ranging also has drawbacks regarding reliability due to positioning and transmission errors if it is applied in a standalone way.

Thus, the solution presented in this paper is a hybrid approach combining autonomous and cooperative methods for detection and ranging within a common architecture. A particle filter is used for the state estimation and sensor fusion. The results are a higher detection effectiveness and a lower position error compared to using standalone autonomous or cooperative detection and ranging methods.

I. Introduction

Today, most traffic accidents occur due to a human false estimation of the current traffic situation which is the consequence of misinterpretation or a limited amount and accuracy of information [1]. Future *Situation-aware Driver Assistance Systems* [2] will support humans in their task of driving a vehicle safely, efficiently and comfortably by exploiting situational information of the own vehicle as well as other information sources (other vehicles, road side units, etc). To achieve this comprehensive situation awareness, information on the presence and position of vehicles in the vicinity is of particular importance. This vicinity includes areas with more or less relevance depending on the type of application. For an application such as Adaptive Cruise Control (ACC) [3] the area in front of the vehicle up to the distance of the preceding vehicle within the same lane is of major relevance. But - migrating more and more to *Predictive Safety Systems* [4] - also adjacent areas are of increasing relevance. E.g. knowing the presence and position of vehicles located on adjacent lanes or in front of the preceding vehicle may be relevant in order to be prepared for abrupt lane change maneuvers or full braking of the preceding vehicle respectively (see fig. 1). Key enabler for future driver assistance is hence a complete and accurate model of the surrounding including each individual vehicle within the relevant scope because even having no or inaccurate information of a single vehicle may result in a perilous situation.

In order to gather information on the surrounding vehicles, methods for detection and ranging are required. Detection and ranging of objects in the scope of this

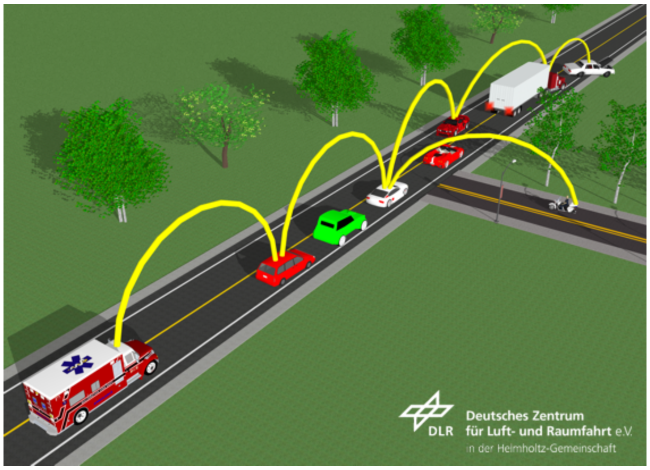

Fig. 1. Multi-hop Vehicle-2-Vehicle communication: Due to a broken down vehicle a truck has to brake hard. Without Vehicle-2-Vehicle communication the following vehicles will have no information on the hazardous situation in time because of the highly obstructed view.

paper means the determination of presence and position of these objects relative to the ego vehicle. This information can then be used in a multitude of applications, e.g. ACC, hazardous following distance warning, frontal/rear-end/flank collision avoidance, merging assistance, etc [5].

Objective of novel detection and ranging methods is to increase the *Detection Effectiveness* and decrease the *Position Error* at the same time. This paper will present a novel concept for a hybrid approach combining autonomous and cooperative detection and ranging.

Section II gives an overview of concepts and types of detection and ranging methods for vehicles. Causes of error that will play a major role for the proposed algorithm will also be detailed herein. The proposed algorithm for a hybrid approach combining autonomous and cooperative detection and ranging methods is provided in section III. Initial simulation results are presented in section IV. The paper ends with conclusions and outlook in section V.

II. Detection and Ranging Methods

In principle, two different types of detection and ranging (DaR) methods have to be differentiated:

- **Autonomous detection and ranging:** Detection and ranging is performed only by the ego vehicle without active interaction of the target vehicle. The target vehicle stays completely passive.
- **Cooperative detection and ranging:** Detection and ranging is performed in a cooperative way by information provided by the target vehicle. The target vehicle plays an active role.

A. Autonomous Detection and Ranging

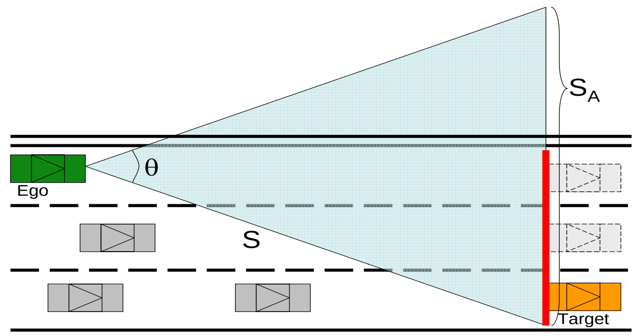

Fig. 2. The figure shows a traffic situation on a 3-lane (per direction) road with several vehicles. The ego vehicle detects one target vehicle with its radar sensor. But there may be more vehicles with the same range which can not be separated and therefore are merely sensed as a single vehicle.

a) Radar: A common mechanism of autonomous DaR of objects is the measurement of transit times of electro-magnetic signals. This concept is exploited for instance by the well-established *radio detection and ranging (radar)* system which uses micro waves with a wave length of 1 millimeter up to several meters. Radar systems deployed as in-vehicle sensors use for instance the following frequency bands regulatively assigned in Europe (according to [6], [7]):

- K-band at 24 GHz for *short range radar* applications (conferred until 2013 [8])
- W-band at 79 GHz for *short range radar* applications (conferred for future usage [9])
- W-band (76-77 GHz) for *long range radar* applications [10], [11]

For the increased situation awareness required for future *Situation-aware Driver Assistance Systems* particularly *long range radar* technology is of major importance. *Long range radar* is aimed at maximum distances up to several hundreds of meters. The maximum distance R_{max} can be calculated by the following equation (according to [7]):

$$R_{max} = \sqrt[4]{\frac{P_{Tx} \cdot D^2 \cdot \sigma}{P_{min} \cdot 4\pi \cdot \lambda^2}} \tag{1}$$

P_{Tx}	Transmit Power
D	Effective length of the antenna
σ	Reflectivity of the target
P_{min}	Minimum power necessary for detection
λ	Wave length of the signal

In addition to the maximum distance of the DaR technology, the azimuth angle of beam spread is an essential characterization parameter in order to determine the sensor scope. The half-power beamwidth θ depends on the wave length λ and the effective length of the antenna D. It can be calculated by the following equation (according to [12]):

$$\theta = K\frac{\lambda}{D} \tag{2}$$

K is known as the beamwidth factor (e.g. $0.88\ \mathrm{rad} \sim 50.76^\circ$ for uniform distribution rectangular apertures [13]).

The angular resolution S_A of a radar, which defines the minimum distance at which two equal targets at the same range can be separated, can be calculated by (see fig. 2):

$$S_A \geq 2S \cdot \sin(\theta/2) = 2S \cdot \sin(\frac{K\lambda}{2D}) \tag{3}$$

S	slant range along half-power beamwidth

The radar sensors available on the market today suffer from low angular resolution because of a half-power beamwidth of more than 6° due to aperture size limitations. According to Rasshofer et al. [14] this results in poor target separation in long and medium ranges. As an example, the angular resolution in a slant range of $150\ \mathrm{m}$ according to equation (3) is more than $17\ \mathrm{m}$ and thus spans at least over the two adjacent lanes with a lane width of $3.50\ \mathrm{m}$ according to German standard cross-section RQ-33 [15] for a 6-lane autobahn (as it is shown in fig. 2). An application such as ACC can not adapt the optimal speed in this situation because it cannot infer whether there is one or more vehicles within the relevant scope.

Modern radar sensors use filter techniques to overcome the problem of poor angular resolution but show constantly significant measurements errors, target losses or ”ghost targets”. Figure 3 shows periodic radar measurements (distance measurements encoded in stem length) recorded on a real test run. The real distance to the target vehicle is depicted as horizontal solid line.

b) Lidar: Another autonomous DaR method which uses laser instead of microwaves is called *light detection and ranging (lidar)* system. Due to its high frequency, lidar has a highly directional signal propagation and shows a much higher angular resolution. But, in contrast to radar which do not show significantly deterioration in fog, rain or snow, lidar sensors show high sensitivity towards these environmental influences.

B. Cooperative Detection and Ranging

In contrast to autonomous DaR methods, the target vehicle is actively involved in cooperative DaR. Therefore, the target vehicle cooperates with the ego vehicle by transmitting messages with position relevant data. By receiving the position relevant information, the ego vehicle can calculate the relative position of the target vehicle. So, basically, cooperative DaR comprises three main steps:

(1) Self-positioning of both ego vehicle and target vehicle within a common reference system
(2) Transmission of the target vehicle’s position to the ego vehicle
(3) Range calculation by the ego vehicle

These steps will be described more in detail in the following paragraphs:

a) Self-positioning: A promising solution for self-positioning is the *Global Navigation Satellite System (GNSS)* because of its global availability in outdoor areas. Although GNSS is the most promising solution for positioning vehicles at present, other variants have to be mentioned as well, e.g. GSM/UMTS signal measurements or dedicated road infrastructure, but are not further studied in this paper. More information on general concepts of self-positioning can be found in [16].

GNSS is based on lateration of undirectional *Time of Arrival (ToA)* measurements and therefore several measurements from different satellites are required to get a complete position estimation. With elimination of impossible solutions at least two measurements to individual non-collinear satellites for a 2D positioning or three measurements for a 3D positioning are required. Normally, a further satellite is necessary for time synchronization between the space segment and the user terminal.

The ToA measurements of the user terminal can be based on two different levels:

- Code based measurements: ToA is measured on code level (synchronization on chip basis)
- Carrier based measurements: ToA is measured on carrier level (synchronization on carrier phase basis)

Sources for inaccuracy are up to delays in signal runtime resulting in erroneous pseudorange ρ calculation:

$$\rho = c\Delta t = c(\Delta\tau + \Delta\delta) = \varrho + c\Delta\delta \tag{4}$$

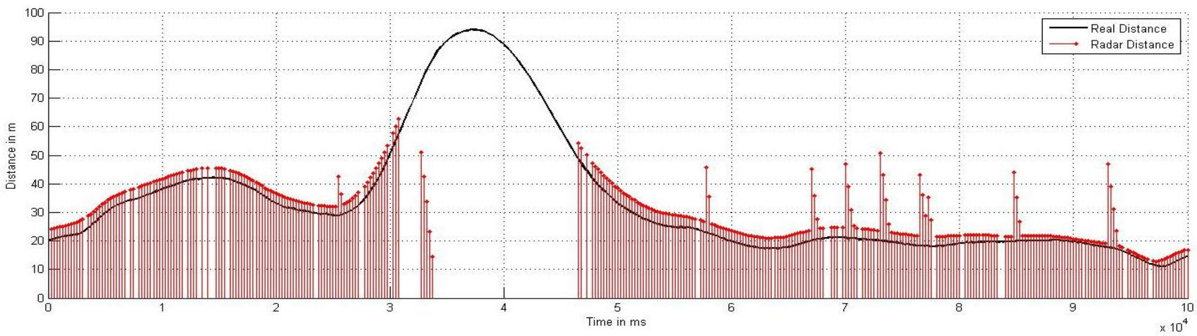

Fig. 3. Radar distance measurements

c is the velocity of signal propagation, $\Delta\tau$ is the theoretic signal transit time following line of sight, ϱ is the true geometric range and $\Delta\delta$ is the additional signal transit time that emerges due to satellite clock offset, satellite orbit dislocation, ionospheric and tropospheric refraction, receiver clock offset and multipath propagation. The former two error types, i.e. satellite clock offset and orbit dislocation, are specific to a certain satellite and only depend on this satellite. Atmospheric refraction errors depend on satellite and receiver position. Receiver clock errors and multipath errors strongly depend on the receiver and its local environment.

b) Position transmission: To inform the ego vehicle of position relevant data in time, the target vehicle requires a reliable communication channel which allows fast channel access and transmission times. Due to channel setup delays and infrastructure as prerequisite, cellular systems (e.g. GSM/UMTS) are suitable to only a limited extent. Preferable is ad-hoc networking with fast channel access schemes such as Vehicle-2-Vehicle (V2V) communication based on Wireless LAN.

Wireless LAN based V2V communication is currently in the standardization process under *Wireless Access for Vehicular Environments (WAVE)* including IEEE 802.11p and IEEE P1609.1-4 in the U.S. and under ETSI TC ITS and the Car-2-Car Communication Consortium in Europe. Besides unicast and multicast as data distribution mechanisms geo-based anycast and broadcast addressing will be developed. CSMA/CA is used for medium access control which requires acknowledged message transmission for the detection of transmission errors as a result of packet collisions. In order to avoid the broadcast storm problem broadcasting is not fed back by acknowledgements and thus subject to unreliable message transmission. Packet loss strongly depends on the channel load which is influenced by the number of channel accesses, the message length and the number of vehicles within the network. The maximum allowed power will be between 33-44 dBm EIRP with an expected range of up to 1000 meters. The absolute range for message transmission can be extended by multi-hop messaging.

c) Relative position calculation: The position relevant information sent by the target vehicle can then be used to calculate the position of the target vehicle relative to the ego vehicle. Basically there are three different types of relative positioning:

- **Absolute position based relative positioning** by differencing of two absolute positions. Target vehicle and ego vehicle have to agree on a common reference system, such as WGS-84. This method may be influenced by the whole set of GNSS measurement errors described above.
- **Code based relative positioning** uses a *Time Difference of Arrival (TDoA)* method with several simultaneous measurements on chip basis (see above). Ego vehicle and target vehicle have to use identical satellites at the same time. Depending on the algorithm the following errors can be eliminated:
  - Single differencing between receivers eliminates pseudorange errors emerging from satellite clock bias, satellite orbit dislocation and ionospheric and tropospheric refraction. The different types of errors have a high correlation when signals emitted from the same satellite at the same time have a similar propagation path which is valid within short distances between ego vehicle and target vehicle as it is considered in this paper.
  - Double differencing between satellites additionally eliminates errors emerging from re-

ceiver clock offsets.

- **Carrier based relative positioning** uses TDoA on a carrier phase basis. Besides single and double differencing, triple differencing between epochs has to be considered in order to quantify integer cycle ambiguity.

Depending on the type of algorithm used for cooperative relative positioning, different types of position relevant data has to be transmitted between the target vehicle and the ego vehicle. Whereas absolute position based relative positioning has lower acccuracy but can be encoded in a few bytes (e.g. 2x2 bytes (Latitude-Longitude) according to [17]), pseudorange based relative positioning has higher accuracy but requires about 10 times as much data to encode (e.g. 8x5 bytes = 8 pseudorange measurements encoded in 5 bytes). Carrier phase based relative positioning has a even higher accuracy but requires considerably longer messages. Evidently, for reaching higher accuracy longer messages have to be accepted. Thus for the final protocol specification a respective tradeoff between message length and position accuracy has to be defined.

III. Hybrid Detection and Ranging

Goal of DaR methods that conform to requirements of a *Situation-aware Driver Assistance System* is to gain an effective and accurate position estimation of all target vehicles within the relevant scope. Due to the errors of DaR methods as described in the previous section, a single DaR method is not capable to fulfill the requirements continuously in every situation. Therefore the combination of different DaR methods which complement each other is considered as a promising solution.

A lot of work has already been done in fusioning of different autonomous systems (e.g. radar & lidar) but all these systems mainly suffer from a common subset of error causes which have strong influence on effectiveness and accuracy. Examples as described in the previous section are the shadowing by obstacles (e.g. in road curvatures), sensitivity towards environmental influences (e.g. fog, rain, snow) and a narrow detection zone. On the other hand, cooperative DaR depends on the active participation of the target vehicle and therefore strongly depends on the penetration rate as well as the effectiveness and accuracy of self-positioning and the wireless transmission of position relevant information.

The hybrid approach presented in this paper therefore combines autonomous and cooperative DaR methods in a hybrid approach including an adaptive sensor fusion. The outcome of this is an increased effectiveness and higher accuracy which will be shown in the simulation results in section IV.

A. Reliable and accurate target tracking

Core component of our hybrid approach is the time-discrete value-continuous sensor fusion algorithm for the combination of autonomous and cooperative DaR. Independently of the type of sensor, measurements are subject to incompleteness and inaccuracy. Therefore, the preferred fusion algorithm should filter the noisy sensor measurements $\mathrm{z}_i^{1:k}$ for sensor $i = 1, \ldots, n$ over time $1 : k$ and adequately infer the variable of interest x^k at time k. The variable of interest for DaR comprises at least the relative position of the target vehicle. For our implementation the state space of the variable of interest is spanned by a heading aligned 2-D cartesian coordinate system. The relative position of the target is hence formalized by $\mathrm{x}^k = [x_{lat}^k, x_{lon}^k]$, i.e. the latitudinal and the longitudinal intercept. Analogously, the sensor measurements of the i-th sensor is formalized by $\mathrm{z}_i^k = [z_{lat}^k, z_{lon}^k]$ which are the autonomous DaR sensor and the cooperative DaR sensor in our case.

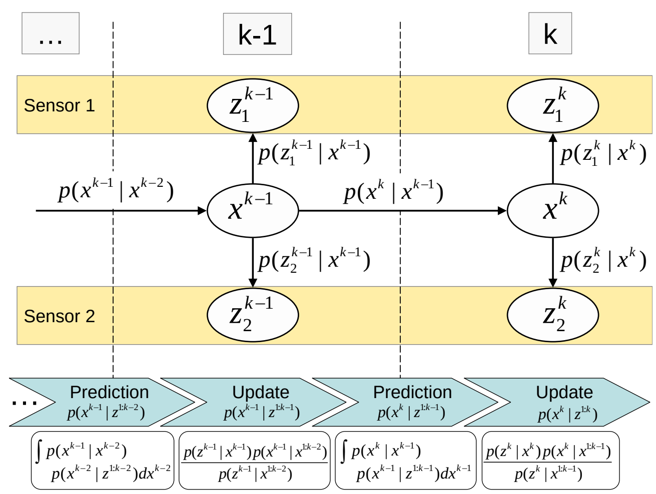

Fig. 4. Bayesian state estimation with two sensors

"From a Bayesian perspective, the tracking problem is to recursively calculate some degree of belief in the state x^k at time k" [18] given evidence $\mathrm{z}^{1:k}$ (see fig. 4). The degree of belief is characterized by the probability density function (pdf) $p(\mathrm{x}^k|\mathrm{z}^{1:k})$. This pdf can be obtained, recursively, by a two-phase approach: prediction and update.

The prediction phase of the dynamic state estimator is defined by:

$$p(\mathrm{x}^k|\mathrm{z}^{1:k-1}) = \int p(\mathrm{x}^k|\mathrm{x}^{k-1})p(\mathrm{x}^{k-1}|\mathrm{z}^{1:k-1})d\mathrm{x}^{k-1} \quad (5)$$

The update step is defined by:

$$p(\mathrm{x}^k|\mathrm{z}^{1:k}) = \frac{p(\mathrm{z}^k|\mathrm{x}^k)p(\mathrm{x}^k|\mathrm{z}^{1:k-1})}{p(\mathrm{z}^k|\mathrm{z}^{1:k-1})} \quad (6)$$

To solve the equations, different types of Bayesian filtering can be applied, including kalman filter and its extensions or the particle filter. In order to meet the requirements of a dynamic flexible state estimation, we chose particle filtering because it allows the usage of non-Gaussian measurement and movement noise and non-linear measurement and movement models [19], [18], [20]. Especially for complex non-linear driver behavior modeling (e.g. the Generalized GM model [21]) this is an essential requirement.

Particle filtering is a sequential Monte Carlo method which represents the posterior distribution of the state estimation by a set of discrete samples, so called *particles*. Particle filtering belongs to the category of suboptimal filter algorithms which merely calculate an approximation of the variable of interest but allow non-linearity in the movement and sensor model (in contrast to the standard kalman filter). Our fusion approach is based on the *Sample Importance Resampling (SIR)* algorithm which is a special case of the *Sequential Importance Sampling (SIS)* algorithm. For each time slot k the variable of interest is represented by a set of m particles $s_j^k, j = 1, \ldots, m\}$ and the corresponding weight w_j^k of the particle. With a sufficiently large number of particles the SIS filter approaches the optimal Bayesian estimate.

Even in situations where merely a single sensor is available, i.e. if the target vehicle is for instance not equipped with cooperative DaR, the dynamic state estimation allows promising results. But in every case additional information becomes available, effectiveness and accuracy can be increased significantly by sensor fusion combining the sensor measurements. Simulation results will be shown in section IV.

a) Measurement transformation: In the run-up to the fusion algorithm itself the independent measurements have to be transformed to a common local reference system. This reference system may for instance be a polar or a cartesian coordinate system which may be aligned to a fixed direction (e.g. geographical north pole), dynamically adjusted according to the ego heading or even road-aligned [22]

Originally measurements from autonomous systems are to a certain extent directional and the sensors have a fixed installation location and orientation. Thus the measurements are already aligned to the ego vehicle heading and position - possibly with a certain offset in orientation and location. Depending on the type and orientation of the local coordinate system, the measurements have to be transformed adequately.

Cooperative DaR systems are not inherently aligned to the ego vehicle heading. In cases where a heading aligned coordinate system is used the measurements have to be transformed adequately. Therefore the heading of the ego vehicle can be estimated by analyzing the steering angle. In order to determine the initial heading either further sensors, such as compass or gyroscope, are required or the initial heading has to be inferred by consecutive position measurements. For the translocation of the measurements the positioning antennas' location of both vehicles have to be known. Whereas for the ego vehicle the antenna position can easily be determined, the antenna position of the target vehicle has to be standardized or has to be added to the position relevant information that is sent by the target vehicle. Furthermore the target vehicle size has to be annotated in order to allow the ego vehicle to reference the cooperative DaR measurement to the reflection point of the autonomous DaR independent of the target vehicle's heading.

b) Measurement-target association: If several target vehicles are detected, measurements have to be associated. A promising solution for particle filtering is provided by Hue et al. in [23]. Their *Multi Target Particle Filter (MTPF)* combines the two major steps (prediction and update) of the classical particle filter with a Gibbs sampler-based estimation of the assignment probabilities. Another solution which does not perform an explicit measurement-target association is the *Finite Set Statistics (FISST)* by Mahler [24] and the *Joint Multi-target Probability Density (JMPD)* by Kreucher et al. [25]. Their solutions which are based on multiple hypotheses outperforms association-based solutions in situation with high clutter, occlusions and multi-target confusions.

B. System Architecture

The overall architecture of the *Situation-aware Driver Assistance System* using our hybrid approach for DaR is depicted in fig. 5. Principally it uses autonomous and cooperative sensors as main input for the fusion algorithm. In order to predict future movement and align the reference system, further input, such as steering angle sensor and compass is used. The prediction is performed by a *State Model* including a realistic vehicle following model (e.g. Krauss model [26]). Sensor errors are represented by the *Sensor Model*. The results of the fusion, i.e. a reliable and accurate relative position of target vehicles, can then be used in the *Situation Analysis* to detect hazardous or inefficient situations. Last, this is used to adapt vehicle effectors, e.g. adjust the ACC controller or inform the driver by visual, verbal or tactile Human-Machine Interfaces.

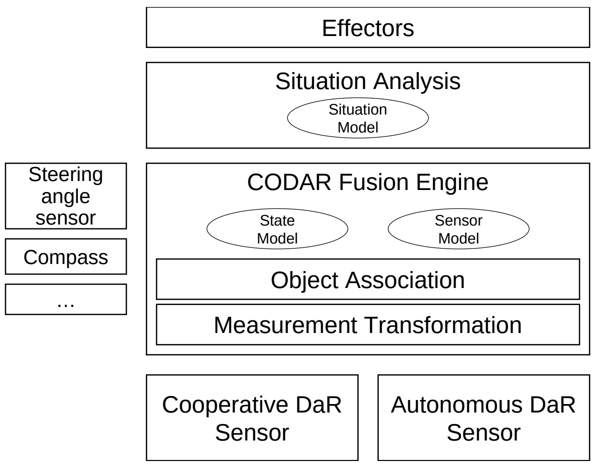

Fig. 5. CODAR Architecture

The described components are part of the *Cooperative Object Detection And Ranging (CODAR)* system which is a framework for information management based on Vehicle-2-Vehicle communications developed by the German Aerospace Center. It includes a comprehensive and integrated set of tools and algorithms for the development of cooperative driver assistance systems aiming at increasing safety, efficiency and comfort of driving. More information on the system architecture and the integration into the Situation-aware Driver Assistance System as a virtual sensor can be found in [27].

IV. Performance Evaluation

A. Simulation Environment

In order to validate our concepts we designed a simulation environment that allows the simulation of cooperative and autonomous DaR in reproducible traffic situations. Real test runs with real sensor measurements were not suitable for our purpose because it is almost impossible to guarantee identical situations for several sequential test runs. Thus, test results would not be comparable.

We therefore designed and implemented a simulation environment enabling the selective usage of autonomous and cooperative DaR sensors. Therefore we implemented a *long range radar* sensor which incorporates the measurement errors described in section II. Thus the quantity of detected target vehicles results from:

`# of detectable vehicles`

vehicles that are within the azimuth angle and in detection range due to equation (1)

$-$ `# of undetected vehicles`

vehicles that stay undetected due to obstacles and angular resolution (eq. (3))

$+$ `# of wrongly detected vehicles`

ghost vehicles that appear due to signal scattering

In the simulation we used a long range radar with 6° azimuth beamwidth. The maximum range for a vehicle detection is $\sim$150 m. Vehicles that are not detected mainly arise due to the reflection of signals on intermediate obstacles and the limited angular resolution. Wrongly detected vehicles occur due to scattering of signals on obstacles (such as guard rails, roadside planting or other vehicles). In our simulations we used a fixed rate of 20% of the number of detectable vehicles for the wrongly detected vehicles. For the quality of each measurement we used a 0-mean Gaussian measurement noise with $\sigma = 2$ m.

The cooperative DaR was based on absolute position based relative positioning with a constant 0-mean Gaussian measurement noise with $\sigma = 5$ m. Transmission errors were not modeled adequately because a small number of vehicles and a high beaconing rate (10 Hz) of position relevant information was used and thus sporadic message losses can be neglected for the overall observation. The medium access and signal propagation delay can also be neglected due to the low number of vehicles. Of course, this has to be inspected in detail for dense traffic situation in the future.

An implementation of the CODAR fusion engine based on a particle filter with 1000 particles has been integrated into the simulation environment. The number of particles plays a decisive role for the state estimation and has to be traded off between accuracy/effectiveness and computability. 1000 particles turned out to have a sufficiently high accuracy/effectiveness and is computable under real-time conditions on a Intel Core 2 Duo (2.2 GHz) with 2GB RAM. For the initial simulations a simple random movement model and basic sensor models were applied.

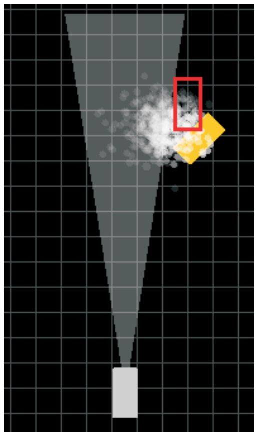

Fig. 6. CODAR Simulation Visualisation

Figure 6 shows a snapshot of the graphical output of the simulation environment. The depiction shows the ego vehicle (bottom) and a target vehicle (top). The white dots represent particles with opaqueness proportional to the particle weight. The overlying rectangle shows the estimated position of the target vehicle based on the minimum mean square error.

B. Quantification Measures

For the quantification of DaR methods we propose two major measures:

a) Detection Effectiveness: The *Detection Effectiveness* is a measure to quantify the effectiveness of the DaR method. Rijsbergen defines effectiveness in terms of *Precision* and *Recall* [28].

Recall is a measure of completeness and specifies the probability that a real vehicle will be detected. It is defined by:

$$\text{Recall} \quad R = \frac{TP}{TP + FN} \tag{7}$$

TP	True Positives → Detected targets that correspond to real vehicles within the relevant scope
FN	False Negatives → Undetected targets that correspond to real vehicles within the relevant scope

Precision is a measure of exactness and specifies the probability that a detected vehicle corresponds to a real vehicle. It is defined by:

$$\text{Precision} \quad P = \frac{TP}{TP + FP} \tag{8}$$

TP	True Positives → Detected targets that correspond to real vehicles within the relevant scope
FP	False Positives → Detected targets that do not correspond to real vehicles, i.e. ghost targets, within the relevant scope

The scope in which the effectiveness is analyzed is determined by the application that requires the information. ACC, for instance, defines the scope as the headway of the ego vehicle up to a certain range that depends on the current speed, the following distance, etc. [3].

b) Position Error: The second measure, the *Position Error*, is a qualitative measure for the accuracy of DaR methods. The *Position Error* is defined by the root mean square error whereas the error is the Euclidean distance between the estimated position and the real position of the target vehicle. It is defined by:

$$PE = \sqrt{E[\ \| \hat{X} - X \|_2\ ]} \tag{9}$$

X	Real distance to the target vehicle
$\hat{X}$	Estimated distance to the target vehicle

C. Simulation Results

In our simulations we focussed on two different scenarios. The first analyzed scenario was similar to the scenario shown in figure 2. The ego vehicle is driving on the left most lane of a three-lane road. Both other lanes are heavily occupied by vehicles with slower speed. Thus the ego vehicle drive past several target vehicles in the observed simulation period of 10 seconds. For this scenario we studied *Recall* and *Precision* based on the requirements of two different scopes. The first scope, depicted in figure 7 and 9, was the scope of a conventional ACC which is the area in front of the vehicle up to the distance of the leading vehicle. The relevant scope of figure 7 and 9 is hence defined by the detection zone of a radar system with 6° azimuth beamwidth and a maximum detection range of ∼150 m.

In figure 8 and 10 we analysed the scope of a future ACC which takes the full headway of the ego vehicle into account. Therefore we used the same range as before, i.e. 150 m, but a larger angle of 180°. This scope will be in particular important for future safety applications that will take all vehicles within the ego headway into account in order to enable accurately timed situation-specific driver assistance.

Figures 7-10 show the absolute number of relevant vehicles (horizontal solid line), the number of detected vehicles by standalone radar (dark gray stem) including false positives (black part) and the number of vehicles detected by our hybrid approach (light gray) in the form of stems at the bottom of each figure. The simulated test drive has a duration of 10s.

Evidently, in figure 7 and 9 the number of vehicles detected by standalone radar is nearly as high as the number of relevant vehicles because of the optimal case that the relevant scope and the scope of the detection sensor is identical. But it has to be recognized that

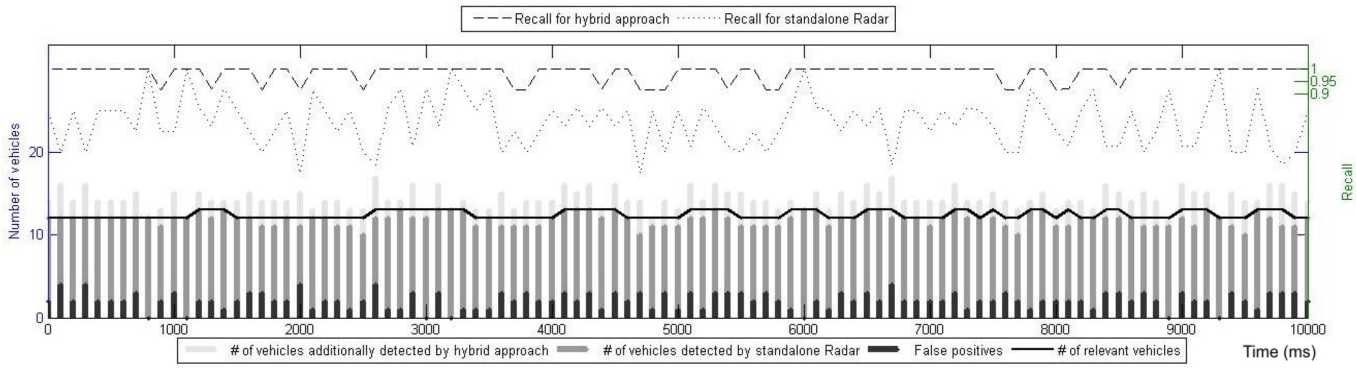

Fig. 7. *Recall* for ACC scope:
The depicted stems in the lower part of the figure show the number of vehicles detected by standalone radar (dark gray) including false positives (black part) and the additional number of vehicles detected by cooperative DaR (light gray). The horizontal line shows the absolute number of relevant vehicles. In the inspected scenario the number of relevant vehicles varies between 12-13 vehicles for the relevant scope of ACC.
On the top of the figure the *Recall* for the standalone and the hybrid approach is depicted. At millisecond 2000 the *Recall* for standalone radar is quite low because the number of detected vehicles (11 out of 12 relevant vehicles) comprises a high number of "ghost targets" (4). The *Recall* thus is $0,5\bar{8}$ meaning that merely slightly more than half of all relevant vehicles have been detected by standalone radar. At millisecond 6000 the radar system detected all 13 vehicles without false positives. Thus the *Recall* for standalone radar its maximum value without the hybrid fusion approach.
But in situations with a low *Recall* of standalone radar, e.g. at millisecond 6700, our hybrid approach can reach a value of 1 (instead of ~ 0.61 with standalone radar) because all vehicles undetected by standalone radar have been detected by the hybrid approach (even with a penetration rate of 80% for the cooperative DaR equipment).

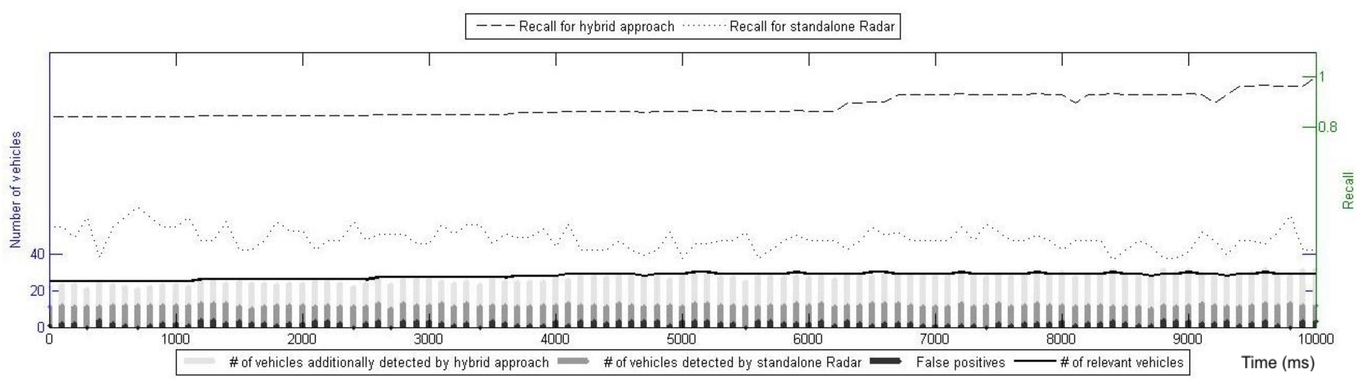

Fig. 8. *Recall* for full headway scope:
This figure differs from fig. 7 by observing a much broader scope, i.e. the full headway scope. The number of relevant vehicles hence is higher than in the preceding scenario (25-30) as depicted by the solid horizontal line. Thus the number of vehicles remaining undetected by standalone radar is considerably higher than with our hybrid approach. The result is a low *Recall* for standalone radar whereas it remains at a high level using the hybrid approach.

this number is affected by undetected vehicles (FN) as well as wrongly detected vehicles (FP). The number of vehicles detected by the hybrid approach hence is composed of:

```
    # of detectable vehicles
 −  # of vehicles undetected by autonomous DaR
 +  # of vehicles wrongly detected by auto. DaR
 +  # of vehicle additionally
      detected by cooperative DaR
```

For the cooperative detection we assumed a penetration rate of equipped vehicles of 80%. Thus, not every vehicle can be detected by standalone cooperative DaR.

To get a more detailed explanation of the depicted simulation results, figures 7-10 also show the results broken down into *Recall* and *Precision*. The simulation clearly shows that the hybrid approach has a more complete (*Recall*) and more exact effectiveness (*Precision*).

Figure 11 shows the *Position Error* of standalone radar in contrast to the hybrid approach. The scenario we

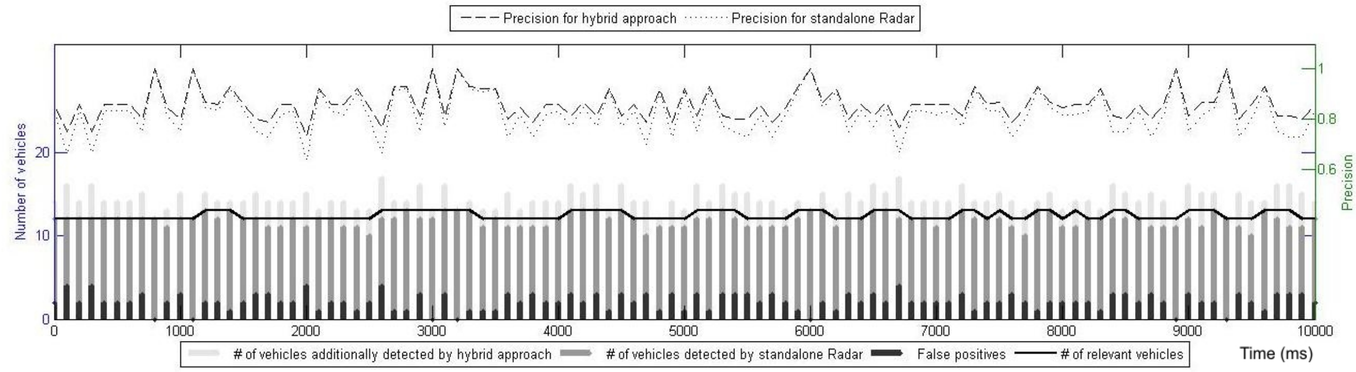

Fig. 9. *Precision* for ACC scope:
Precision indicates the probability that a detected vehicle corresponds to a real vehicle. The inspected scenario is exactly identical to the scenario inspected in fig. 7. Obviously the hybrid approach merely performs slightly better than standalone radar with respect to *Precision*. This can be explained by the number of false positives which remains constant when cooperative DaR is applied additionally to standalone radar. Objects detected by the radar system which are not detected by cooperative DaR cannot be eliminated because the object may be a real vehicle but is not equipped with a cooperative DaR unit.

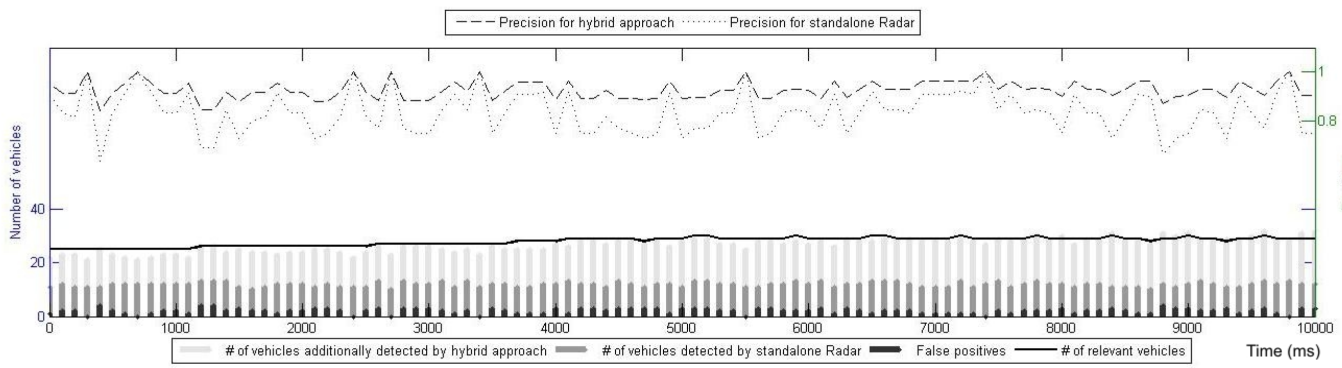

Fig. 10. *Precision* for full headway scope:
The inspected scenario in this figure is exactly identical to the scenario inspected in fig. 8. In situations with few false positives standalone radar performs obviously quite well. But with an increasing number of false positives the *Precision* of standalone radar is considerably worse than with our hybrid approach which remains over 0.9 most of the time.

analyzed was a winding road with no other obstacles or disturbances but a single target vehicle within a constant distance to the ego vehicle. As can be seen in the figure, autonomous DaR shows three measurement losses resulting in high errors when the target vehicle just drove round the bend and thus leaves the detection zone. During these periods the hybrid approach uses cooperative DaR standalone resulting in a higher *Position Error*. When the measurements from the autonomous DaR method get valid again the *Position Error* decreases. Although cooperative DaR has a considerably lower accuracy in our model the hybrid approach shows in almost every case an improvement of the *Position Error* in contrast to standalone radar.

V. Conclusions and Outlook

This paper identifies the main methods for detection and ranging of vehicles and their respective causes of error. In order to overcome these drawbacks a hybrid approach combining autonomous and cooperative DaR has been presented. The fusion of the independent measurements is based on a particle filter as a major part of the CODAR architecture. In order to compare our simulation results and quantify the benefit of our hybrid approach in contrast to standalone radar, we defined two different types of measures, i.e. *Detection Effectiveness*, quantified by *Recall* and *Precision*, and the qualitative measure *Position Error*. The simulation results showed that our concepts significantly increase the *Detection Effectiveness* and decrease the *Position Error*.

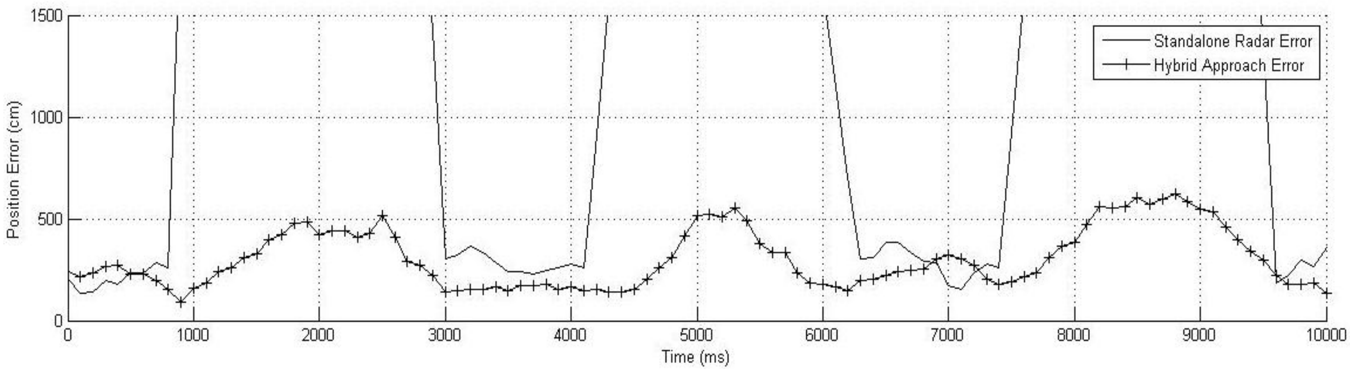

Fig. 11. *Position Error*:
The scenario inspected in this figure is a winding road with 3 tight bends and a single target vehicle running ahead of the ego vehicle with a distance of $\sim 70m$. In situations where both autonomous and cooperative DaR can be exploited (e.g. at millisecond 3000-4100) our hybrid approach has a minor *Position Error* compared to standalone radar most of the time. In situations where the target vehicle can not be detected by standalone radar, the *Position Error* goes to infinity with standalone radar. With our hybrid approach the *Position Error* gets worse in such situations but remains in an acceptable interval (less than 7 meters) for a subset of applications, such as cooperative traffic jam detection [5].

Next steps will be the implementation of more realistic movement and sensor models which will lead to more accurate position estimation. Furthermore we are going to implement a relative positioning method based on code and carrier measurements and compare all three alternatives in our simulation environment in order to estimate their assets and drawbacks. Finally we will deploy our concept in our experimental vehicle and test the hybrid approach under real conditions.

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