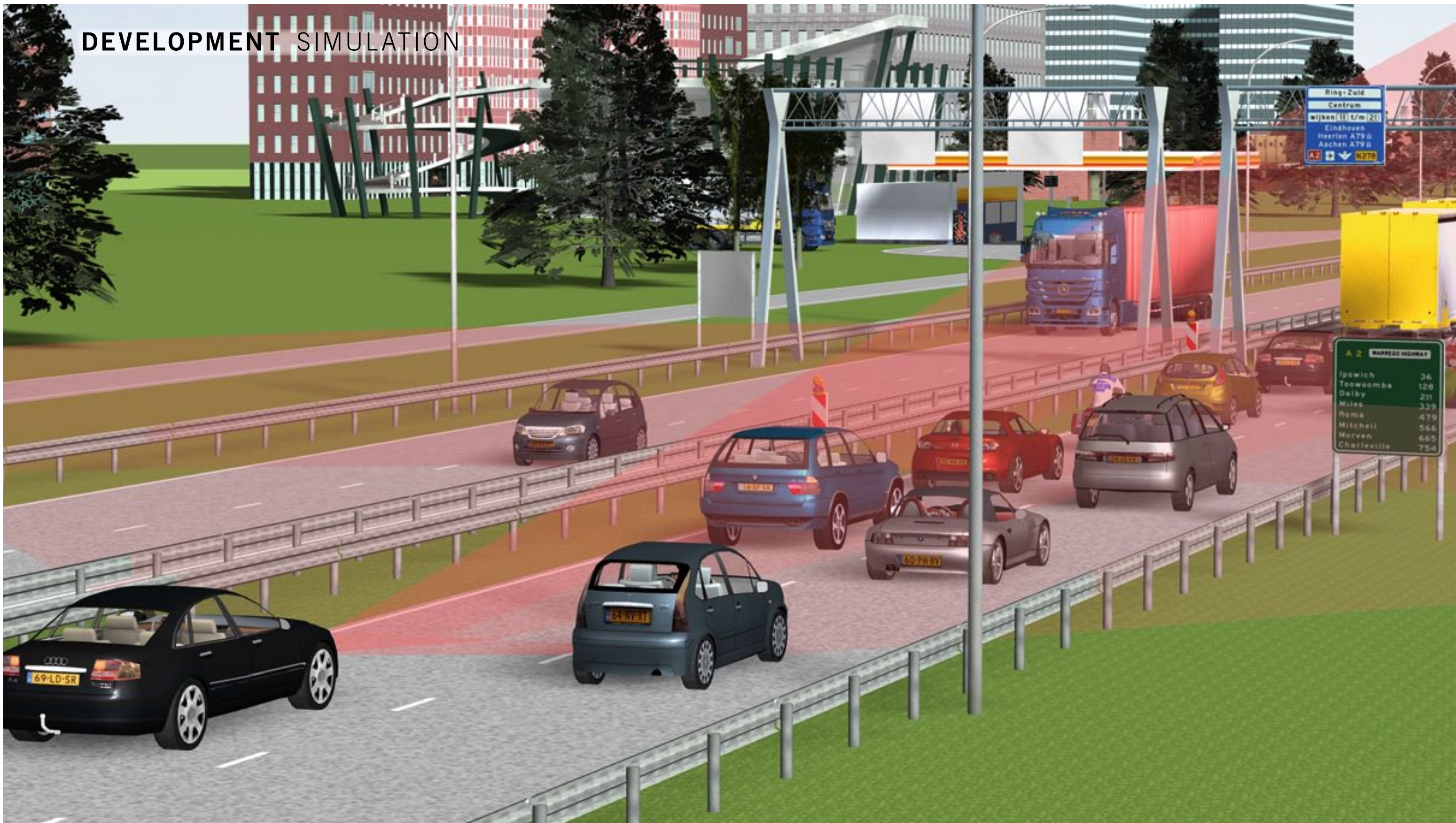

SIMULATION OF SENSOR MODELS FOR THE EVALUATION OF ADVANCED DRIVER ASSISTANCE SYSTEMS

With the increasing deployment of advanced driver assistance systems and the ongoing development of vehicle automation, efficient ways of validating such systems are becoming a crucial part of the development process. In particular, simulations are an increasingly important addition to field trials as they facilitate an early and automated evaluation. In this paper, a probabilistic methodology for simulating sensor data in the context of advanced driver assistance systems and automated vehicles is presented. The objective of this approach is to increase the simulation's level of realism while maintaining both flexibility and adaptability of simulation-based validation strategies. The proposed probabilistic sensor models are compared to real radar data in order to evaluate the statistical characteristics of both data sets. With the presented approach of Baselabs and TASS International, it will be possible to increase the quality of the initial evaluation results based on simulated data.

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MOTIVATION

In order to further increase road safety and traffic efficiency, advanced driver assistance systems are currently being widely deployed. In addition, different stakeholders are currently investigating how an increasing level of vehicle automation can contribute to these objectives [1]. As these systems are directly intervening into the driving process, their design and implementation is highly safety-critical. Appropriate evaluation methodologies are a crucial part of any development process for such systems. Due to the high complexity of traffic scenarios, field trials require a tremendous effort including driving millions of kilometres. Thus, evaluation methodologies based on simulation are increasingly applied – in particular, for the early phases of evaluation. The main benefits of simulations include the possibility to automate tests, to conduct evaluations even if the platform (e.g. sensors) are not yet available and to assess safety-critical situations.

On the other hand, the significance of simulation-based evaluations strongly depends on the quality of the simulations, that is, on the probability that real and simulated traffic scenarios would trigger a similar behaviour of the system under test. Currently, two main approaches of simulating sensor data are being used:

- Ground truth sensor models: These models deliver the true, undisturbed simulated values of the simulated quantities (e.g., the position and velocity of vehicles or the curvature of a lane). The motivation behind this kind of models is that a system which fails on idealised data will certainly not fulfil its requirements in realistic scenarios.
- Physics-based sensor models: These models attempt to cover the internal behaviour of the sensor and the physical measurement principle. As an example, many simulation environments provide rendered camera images that account, among others, for lighting and weather conditions. Similarly, physical radar sensors exist that calculate the propagation of electromagnetic waves in the traffic scene and the detection characteristics (e.g., the antenna patterns) or the sensor.

While each of these approaches is justified for certain use cases, both levels of modelling have particular drawbacks. The disadvantage of ground truth models is rather obvious, as they completely neglect sensor disturbances which deteriorates the significance of the evaluation results obtained with such models. Though physical models appear to overcome this limitation by maximising the realism of the simulated data, their drawbacks are rather a very high computational complexity and – even more important – a rather limited possibility to adapt the simulation to different sensor types. In fact, exchanging, e.g., a Doppler radar by a frequency modulated continuous wave (FMCW) radar implies to develop a completely new physical sensor model.

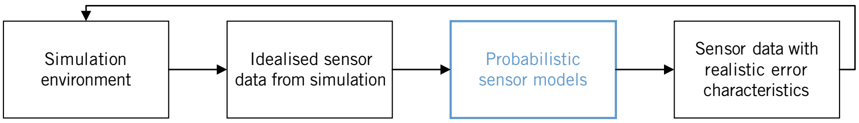
In this paper, an intermediate abstraction layer for sensor simulations is presented which integrates sensor disturbances probabilistically. Thus, the objective is to represent the error statistics of real sensor data rather than the data themselves. ❶ gives a comparison of this approach and the two classical modelling layers. The paper describes the technical approach and presents first results that have been obtained by comparing probabilistically simulated data to real data in a typical traffic scene.

TECHNICAL APPROACH AND CHALLENGES

The general idea of the presented approach that is illustrated in ❷ appears rather straightforward: The idealised sensor data generated from a ground truth sensor model are superimposed by an error signal using a random genera-

CRITERIA	GROUND TRUTH MODELS	PHYSICAL MODELS	PROBABILISTIC MODELS
Error characteristics	Idealised	Realistic	Realistic statistics
Computational complexity	Low	Very high	Low
Adaptability to specific sensors	n/a	Very low	High

❶ Comparison of different abstraction layers of sensor models for simulation



❷ General structure of the probabilistic sensor model approach

❸ Comparison of real and simulated traffic scenario used for the evaluation

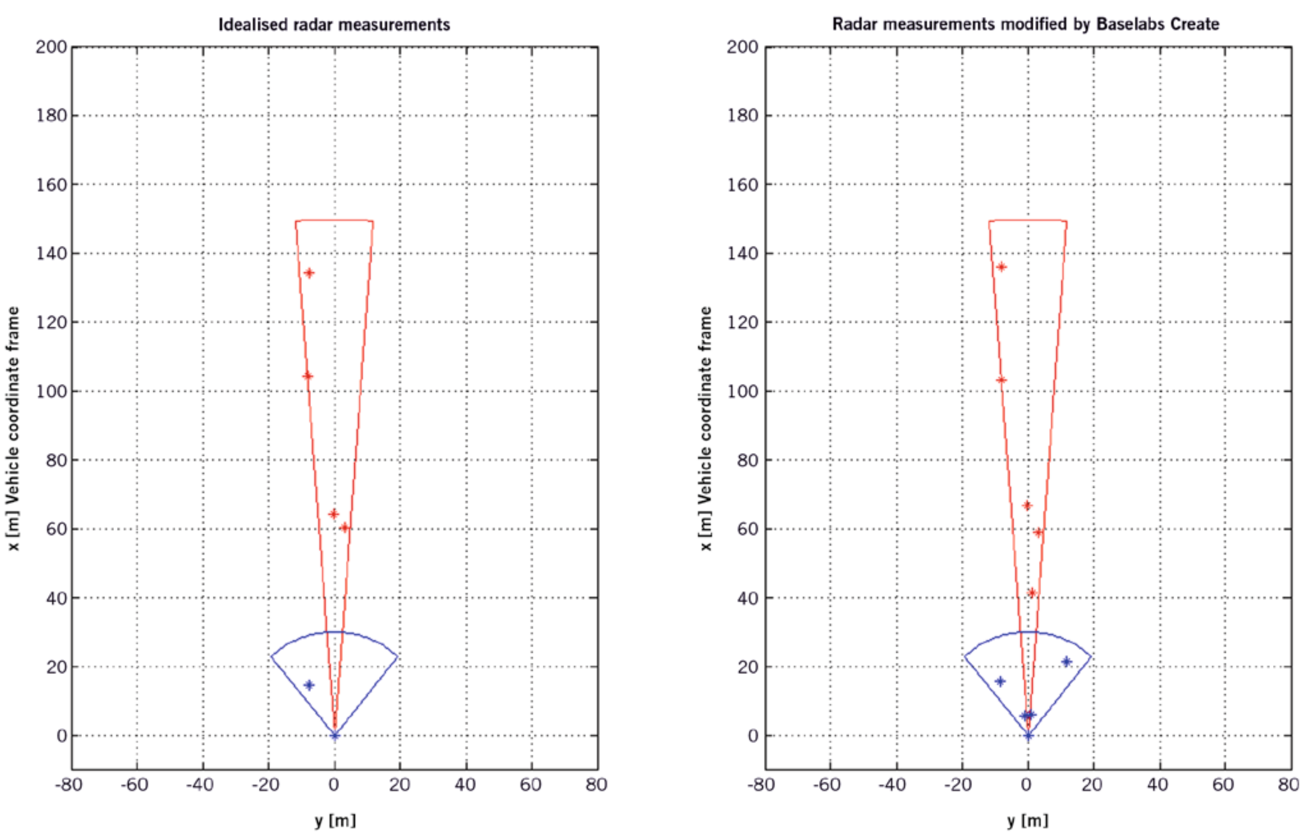
tor. In practice, this can be done using a Monte Carlo approach (for instance, rejection sampling [2]). This approach can be applied to different types of sensor errors, including:

: white/coloured sensor noise
: false positive detections (that is, detections not based on a true object)
: false negative detections (that is, objects that do not trigger a detection).

The major challenge is to select an appropriate probabilistic density function (PDF) to sample from. This PDF needs to represent the real characteristics of the sensor while still facilitating adaptability. This adaptability shall not only cover different sensors, but also different environments, weather conditions, etc. This trade-off is achieved by defining a particular type of PDF for each error type (e.g. a Poisson distribution for detection error or a Rayleigh distribution for radar detections). However, the parameters of these PDFs (e.g., the clutter density for a Poisson distribution) can still be set according to the sensor to be represented or the current scenario.

EXAMPLE

In order to approach this challenge, TASS International and Baselabs GmbH are currently working on a joint technical solution based on the solution previously described. The following example gives an impression of this work. For evaluation purposes, data from various sensors have been recorded using the data handling framework Baselabs Connect [3]. The data includes camera images, CAN bus frames and detections of a 77 GHz FMCW radar. From these recorded data, a simulation scenario has been derived using the simulation software



❹ Idealised and modified radar measurements

PresScan [4]. Vehicles in front of the ego vehicle have been simulated using a ground truth position and velocity sensor, ②. These measurements are idealised in the sense that they do not account for sensor noise or detection errors.

Using the approach presented in this paper, sensor noise has been added to the range, range rate, and azimuth measurements of the radar ground truth data. In addition, detection errors including false negatives and false positives (clutter) have been added using a Baselabs-plugin for PreScan, ❸.

❹ shows the results of this example. The most important observation is that the modified sensor measurements contain false alarms, which are the most critical error source for ADAS functions. Those measurements could not be used for testing the robustness of a function on such errors or a perception algorithm that is designed to filter out such errors. In summary, the approach provides less idealised conditions for testing and evaluation and, thus, contributes to a higher robustness of the systems under test.

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