Deliverable D1.3

Final Report

Dissemination level	PU
Version	1.0
Lead contractor	DAI
Due date	31.05.2018
Version date	11.07.2018

This project is co-funded
by the ECSEL JU

Document information

AUTHORS

This deliverable originates from the collective contribution of a group of authors participating in all the RobustSENSE work packages.

Coordinator

Dr. Werner Ritter

Daimler AG

Wilhelm-Runge-Straße 12

89082 Ulm

Germany

Phone: +49 731 505 2140

Email: Werner.R.Ritter@Daimler.com

Project funding

H2020-EU.2.1.1.7.

ECSEL Programme

Contract No. 661933

Legal Disclaimer

Table of contents

List of figures

Executive Summary

RobustSENSE is a collaborative project funded by the European Commission under the ECSEL JU. It is composed of 15 partners including OEMs, scientific organisations and public entities from 5 European countries.

Automated driving is one of the technological mega-trends in automotive industry today. Semi-autonomous vehicles (SAE L3) are planned to be introduced on the market in a few years. Already today, partial automation is taking a role in normal driving (e.g. highway, intersection, etc.). The main challenge, which still remains, is the reliability and robustness of the sensor systems in all possible environmental conditions which can be a challenge for a human driver - also in conditions where driver support is especially needed.

This document contains a high level description of the project collaborative work in terms of goals, achievements and results. We first discuss the project's context and the reasons behind the need for a sensor platform followed by a brief overview of the project's vision and objectives. Next we analyse the architectural requirements and describe the designed validation criteria and metrics. We then proceed to describe a state-of-the-art architecture with four layers, detailing the roles of the main components, their interactions, and the interfaces through which they operate. We also briefly discuss the different major sensor developments and specific innovations in order to give a realistic overview of what was achieved in terms of reliability of automated and autonomous driving functions for safe operation under all driving conditions.

Chapter 7 highlights the perspectives of exploitation, addressing both technology and market aspects. Finally, a concluding section in chapter 8 reports about the major lessons learnt in the project with the aim to provide guidance for future initiatives.

The project vision is a robust and reliable sensor platform for automated and assisted driving that will keep on working in harsh environmental conditions like snow, rain or sun-flare. While many of automated driving enabling technologies are still in a developmental or testing stage, advantages of the systems are visible: the ability to constantly scan the road for other vehicles, pedestrians, bicyclists, and potential hazards, and accurately navigate via a combination of onboard sensors and GPS data.

The objective of the RobustSENSE project was to focus on the development of essential components and sensors for the realisation of sensor data fusion, scene understanding, behavioural planning, trajectory planning and improved sensor technologies. Furthermore, by implementing the resulting sensor platform in the demonstration vehicles, it showcased the potential these novel technologies will have in future driver assistance functions which are far more robust against adverse weather and light conditions.

Consequently, the main technical goal was to define, develop and evaluate measures for detecting performance degradation and reacting to adverse conditions on every level of an automated system all the way from a sensor level up to a strategy planning.

The project architecture was designed to have a generic nature. It is scalable up for new sensors, modules or interfaces which cannot be foreseen today.

The RobustSENSE system architecture is built on different layers. The layers relate to the data/information flow within an intelligent sensor system reacting to real world conditions, managing diversity and complexity:

- **Sensor layer**: Sensor level components (hardware and software) and their output signals. Exact format of the sensor signal is not defined to remain flexible for new sensor units.
- **Data fusion layer**: Having both low level sensor fusion for raw sensor data and high-level fusion modules for fusing object level data.
- **Understanding and planning layer**: This takes care of scene understanding and decision making concerning desired vehicle control and intervention functions and planning of the right trajectory.

All layers include performance assessment sub-modules, checking whether their performance over the time remain and correspond to the initial parameters. In addition, the specific system performance assessment sub-module exists for having overall assessment of the vehicle capability to survey the actual driving conditions. This is the most important contribution of RobustSENSE for increasing situation awareness performance of future autonomous vehicles.

The key result from the RobustSENSE project was the introduction of reliable, secure, trustable sensors and software by implementing self-diagnosis, adaptation and robustness. A core concept of the project was to use ”metrics” to measure sensor system reliability at every level of an assistance and automation system.

1 The project context

1.1 What is vehicle perception

RobustSENSE was a collaborative project funded by the European Commission under the ECSEL JU. It was composed of 15 partners including OEMs, scientific organisations and public entities from 5 European countries.

In this section, we offer a brief description of what constitutes environment perception on automated vehicles (AV).

Perception is the process of transforming measures of the environment into an internal model. The kind of model (and the choice of the sensors) depends on the application. The advances in the field of AVs in recent years have been significant. The extent to which a vehicle is automated can vary from fully human operated (SAE L0) to fully autonomous (SAE L5). The SAE J3016 standard (1) introduces a scale from 0 to 5 classifying vehicle automation.

To be able to release safe and reliable automated driving in real-world traffic, precise and comprehensive perception of the environment is fundamental. For perceiving the environment, today's AVs use a combination of vehicular sensors. Several projects over the past 30 years have been carried out to push forward the development and testing of algorithms for environment perception and navigation of AVs. The main functions of environment perception for AVs are based on a lane and road detection, traffic sign recognition, vehicle tracking and scene understanding.

One main requirement on AVs is that they need to be able to perceive and understand their surroundings in real time. It also faces the challenge of processing large amount of data from multiple sensors such as camera, radar or LiDAR. With perfect perception with a combination of sensor data gathering and interpretation of this data AVs would plan and act perfectly, achieving the reliability and robustness needed for higher level automation (SAE 4 and 5).

1.2 RobustSENSE vision

The RobustSENSE vision is a robust and reliable sensor platform for automated and assisted driving that will keep on working in harsh environmental conditions like snow, rain or sun-flare. While many of automated driving enabling technologies are still in a developmental or testing stage, advantages of the systems are visible: the ability to constantly scan the road for other vehicles, pedestrians, bicyclists, and potential hazards, and accurately navigate via a combination of onboard sensors and GPS data. These autonomous guidance systems also interact with vehicle communication systems integrated in autonomated and traditionally operated vehicles that will share the information on driver actions, traffic patterns, and roadway conditions. As a result, vehicles will perceive the road ahead in far greater detail than a human driver or environment perception sensors alone. By combining these systems and capabilities with the state-of-the-art vehicle construction and physical safety equipment, the autonomated vehicle of the near future may very well represent a major advancement in safe transportation.

RobustSENSE vision is an autonomous vehicle capable of ensuring safe and comfortable travel to its occupants and other road users under all existing driving conditions.

To fully realise the safety promise of driving autonomously and overcome any limitations, new features and robustness should be added to existing systems. Success in these endeavours depend on the vehicle's ability to adapt to driver expectations which will be crucial for winning user confidence and acceptance.

1.3 RobustSENSE objectives

Sensing systems are the most important enablers for adding intelligence in the automotive world. The road to safer driving will require highly precise and real-time information of a vehicle's location and other traffic participants in its surrounding environment.

The main aim of the RobustSENSE project is to:

Develop a sensor platform for automated and autonomous driving, that overcomes the limitations of existing sensors and provides enhanced sensing capabilities.

The RobustSENSE project is focused on the development of essential components and sensors for the realisation of sensor data fusion, scene understanding, behavioural planning, trajectory planning and improved sensor technologies. Furthermore, by implementing the resulting sensor platform in demonstration vehicles it will showcase the potential these novel technologies will have for future driver assistance functions which are far more robust against the influences of adverse weather and light conditions.

Consequently, the main technical goal is to define, develop and evaluate measures for detecting performance degradation and for reacting to adverse conditions – for assistance systems on every level of an automated system all the way from sensor level up to strategy planning.

2 RobustSENSE concept

2.1 Towards a robust sensor system

Sensor systems are vital enablers for understanding of our surroundings and providing with safety to vehicle occupants and other traffic participants. A transformative advance in the field of sensor technology has been the development of sensor elements with embedded intelligence.

A driving goal in the development of the sensor platform is the implementation of a system in a manner that the information is provided to the user wherever and whenever it is needed as well as in whatever form it is needed for the application.

The RobustSENSE project generally aims at the development of an automated vehicle sensorial platform that can operate and ensure the safety of roads users in all environmental conditions.

2.2 Top-level architecture

The project architecture is designed to have a generic nature. It is extendable for new sensors, modules or interfaces which cannot be foreseen today.

The RobustSENSE system architecture is built on different layers. The layers relate to the data/information flow within an intelligent sensor system reacting to real world conditions, managing diversity and complexity. Hence, the architecture is divided into three different layers:

- **Sensor layer**: Sensor level components (hardware and software) and their output signals. Exact format of the sensor signal is not defined to remain flexible for new sensor units.
- **Data fusion layer**: Having both low level sensor fusion for raw sensor data and high-level fusion modules for fusing object level data.
- **Understanding and planning layer**: This takes care of scene understanding and decision making concerning desired vehicle control and intervention functions and planning of the right trajectory.

All layers include performance assessment sub-modules, checking whether the performance over time remains and corresponds to the initial parameters. *In addition, the specific system performance assessment sub-module exists for making an overall assessment of the vehicle capability to survey the actual driving conditions. This is the most important contribution of RobustSENSE for increasing situation awareness performance of future automated vehicles.*

2.3 RobustSENSE structure and work areas

RobustSENSE was a complex project involving 15 partners and closely interrelated activities. In order to properly manage the cooperative work, it was structured into six work packages reflecting the different tasks to be carried out (Figure 2.1).

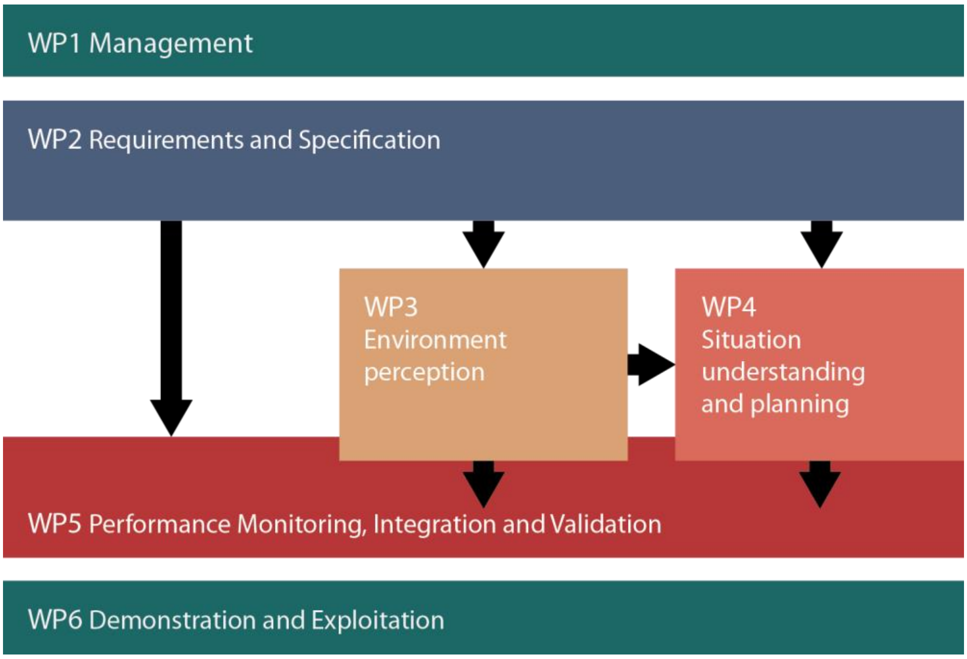

Figure 2.1: The interaction of work packages in RobustSENSE.

Two vertical work packages (WP3 – Environment perception, WP4 – Situation understanding and planning) focused on the actual system development, implementing the lower levels of an environment sensing system for automated driving and becoming the main input for WP4. The latter implemented the upper levels of the sensing system with scene understanding, situation prediction, behavioural planning and trajectory planning.

Horizontal work packages were:

- WP2 laying the foundation for all further technical work in the project by specifying the complete system, its components and the needed interfaces with external modules.
- WP5 dealt with the integration of the soft- and hardware components into a working sensor platform and integration into existing test vehicles.
- WP6 disseminated project advances during the course of the project and prepared the final event which included presenting the demonstrator vehicles to the public.

An additional work package, WP1 Management, was included for handling project coordination, links to external activities and for the general administration.

3 Requirements and specification (WP2)

3.1 Introduction

The orientation phase of requirements and specification laid the foundation for all the technical work. WP2 aimed at creating a common architecture description for the implementation of the modules. This architecture was designed to have a generic nature and is therefore extendable when new sensors, modules or interface which cannot be foreseen today, are available. The RobustSENSE platform consists of the following modules:

1. Sensor layer,
2. Data fusion layer,
3. Understanding and planning layer and
4. System performance assessment.

The primary goal of WP2 was to set up a joint system architecture describing hardware and software components and their specific interfaces. This architecture should describe component properties, data flow and interface data specifications ensuring communication for connecting sensor and application level modules.

In order to realise this goal, it was necessary to describe an evaluation layer. This layer gathered measurements from all the aforementioned components over dedicated interfaces. These measurements served to apply metrics to judge the component and system status. Hence, a reliable set of metrics for performance and reliability measurements on components and system level was specified in WP2 as well.

3.2 Objectives

The main objectives of WP2 were to:

- Gather and manage requirements and specifications for components developed and integrated in WP3, WP4 and WP5.
- Component-wide integration of online- and offline-quality and performance measurement interfaces. These connect the developed components to WP5 components.

The outcome sought in WP2 is the high level architecture whereas use case and sensor specific specifications are dealt with in WP3, WP4 and WP5. This architecture is a general description giving inputs and outputs of all the considered system modules. The RobustSENSE demonstration vehicles may not cover all of the specified modules, but rather showed feasibility and modularity of this approach.

3.3 Key achievements

System Architecture

Architecture specification, metrics definition and validation criteria were designed in D2.1 (Initial System specification) and D2.2 (Metrics and validation criteria). The different sub-modules were specified as well as the interfaces between components. The system architecture follows the general automotive sensor data fusion framework in which system performance assessment modules have been integrated.

The components developed in RobustSENSE needed a common framework to allow collaboration between the partners. Thus, a joint system architecture describing hardware and software components and their specific interfaces was set up.

The generated overall architecture design was investigated in during the first months of the project and described in an early deliverable (D2.1 'Initial system specification'). The framework takes into account the specific hardware and software requirements for automated driving in adverse weather. Component specifications and installation requirements have also been drawn up.

The architecture features the back-bone of the system module development and implementation. The different RobustSENSE pilot vehicles were designed to meet the component specifications. The performance assessment modules were integrated in the different layers of the RobustSENSE system. Based on RobustSENSE architecture, a fusion system was developed as reported in D3.4. The modularity and sensor-set independence of the architecture ensured a continuing functionality even if one or more sensor components fails.

Validation Methodology

A comprehensive validation methodology was generated. This methodology allows a safe and efficient validation of all platform layers without a need for comprehensive real world driving tests in adverse weather conditions.

The structure and interactions between the different elements of the methodology are shown below in Figure 3.1.

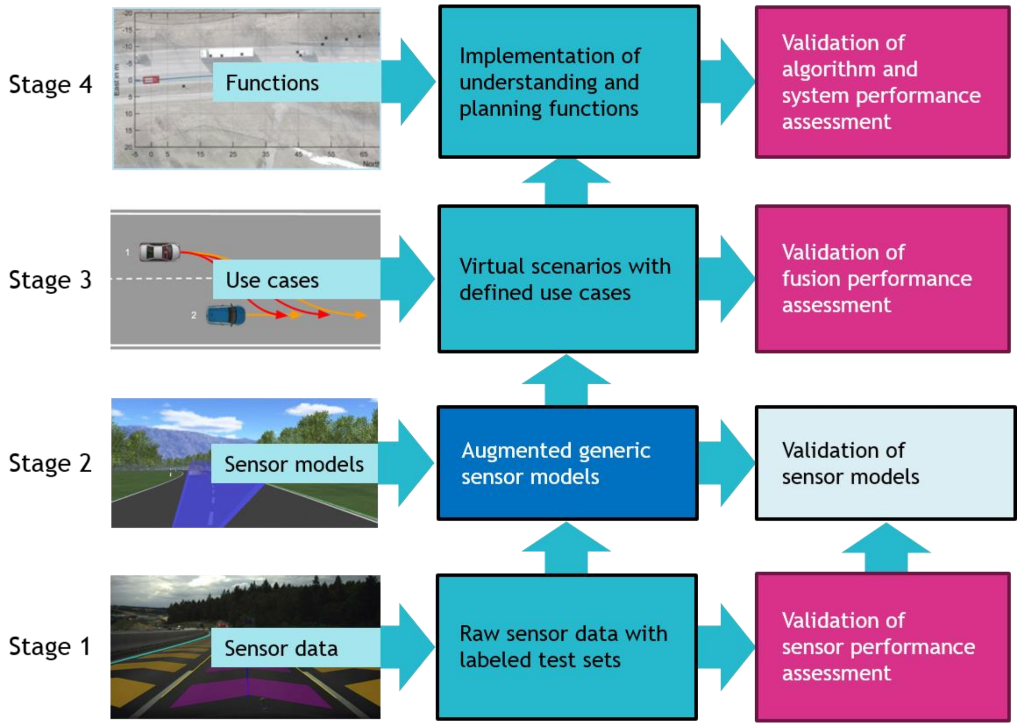

Figure 3.1: RobustSENSE Validation Methodology.

In Stage 1 the implementation of the sensor performance in the different sensor modules was validated with recorded and labelled real world data. The sensor data were recorded either in laboratory or real world driving tests.

In Stage 2 for all specified real sensors on the platform the adequate augmented sensor model was selected and validated with the test results of stage 1.

In Stage 3 the specified critical driving scenarios were selected when already available or newly generated in the test system. The scenarios were then simulated in different weather conditions to validate the fusion performance. For this purpose, the validated sensor models from Stage 2 were used.

In Stage 4 the specified functions of the understanding and planning layer were implemented in the platform and the specified scenarios were simulated. In this stage the algorithm performance of the layer and the performance of the SPAM were also validated.

4 Environment perception (WP3)

4.1 Introduction

The development of environment perception and modelling technology is one of the key aspects for autonomous vehicles (AVs). Upcoming automated driving will only be possible by means of reliable and robust sensing systems. Today, vehicle sensing and environment perception is still an active area of research, and is so far only capable for supporting simple lateral and longitudinal control with the driver constantly monitoring the driving task corresponding to that of SAE L2 driving. Current challenges are the complex outdoor environments and the need for efficient methods for their perception in real time. WP3 aimed at defining a conceptual design of the Environment Model Architecture. The environment perception module is directly addressing among others two of the main problems of the current systems:

- Malfunction of a single sensor often causes deactivation of the complete automated driving function.
- Sensor degradation, e.g. due to foggy and rainy road weather conditions, is treated as a malfunction, and consequently, it is also often causing the deactivation of automated driving functions.

The RobustSENSE system aimed at overcoming the problem of limited perception capability in restricted visibility conditions. Natural characteristics of adverse weather that may affect modern driver assistant systems such as fog, rain, and snow were investigated in a new sensor platform that is able to provide sufficient sensor data even in such weather conditions. This will result in enhancing the weather robustness of current sensors.

Hence, the main aim for WP3 was to exploit redundant sensor information from a multi-sensor platform with distinct measurement principles directly addressing the negative impacts of single sensor malfunction or degradation on perception performance.

4.2 Objectives

The objective of work package 3 was to deliver a consistent environment model including all traffic participants and infrastructure elements with respect to both spatial temporal status and reliability of the information.

Moreover, an overall performance measure of the environment description was delivered.

In particular, WP3 had the following goals:

- Strictly modular system architecture on all levels of information processing,
- Self-monitoring ability on a sensor level,

- Generic quality metric for both, each data item and fused data,
- Data Fusion and Multi-Object-Tracking algorithm able to handle a varying number of input data with changing performance,
- Overall performance value of the present environment model and individual performance measures of all objects included in the environment model.

All modules should be developed and tested in a simulation environment and provided for vehicle integration and assessment in WP5.

4.3 Key achievements

Environment perception modules developed and tested

An environmental perception system architecture was defined together with the relevant project partners. Together with the other consortium partners sensor performance monitoring metrics and an overall performance and reliability monitoring module at an environment model level were defined and specified. Furthermore, the performance of sensors in winter conditions was evaluated including the collection and integration of winter data (i.e. dark, wet, snowy) set into the overall fusion concept.

The analysis of different wavelengths was conducted for adapting the performance of LiDARs for automated vehicles. The spectral responses of different LiDARs were analysed for modifying the components in the existing SICK LD-MRS LiDAR for better penetration in foggy conditions. Fog chamber facilities were used for having exhaustive understanding of different droplet and water content parameter influencing the spectral response. The droplet size and wavelength analysis were carried out in another fog chamber (Figure 4.1) where the parameters could be varied.

Figure 4.1: Fog chamber for LIDAR testing.

The specific spectral measurement devices with illumination and cameras were built-up. The results were analysed and reported (Figure 4.2).

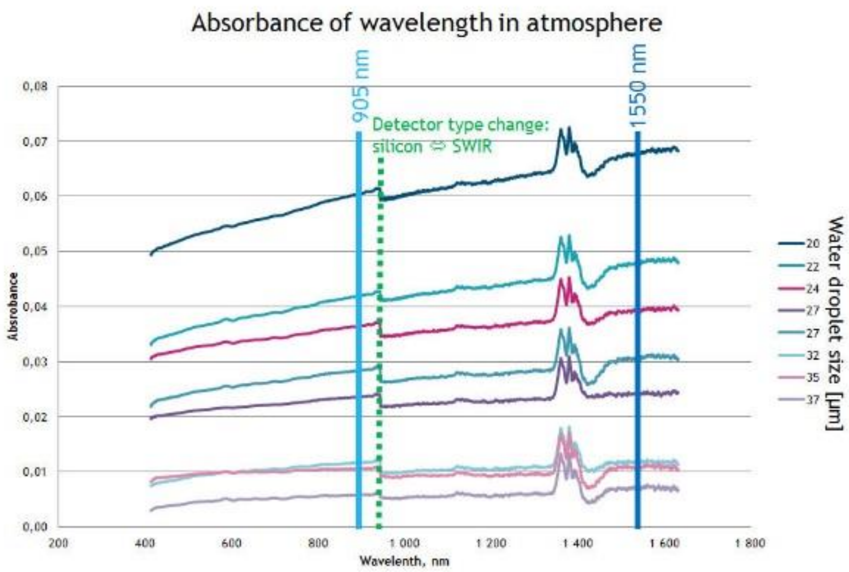

Figure 4.2: Absorbance of wavelength in atmosphere.

The spectral analysis resulted in developing a 4-layer 1550 nm LiDAR for seeing through the fog. The analysis also revealed the narrow SWIR bands (1385 - 1390 nm) where the ambient light from the sun does not absorb light but is still eye-safe. A comprehensive understanding of the temperature influence has been performed.

The implementation architecture fits the reference architecture given in WP2. The focus was on the development of a high level fusion layer with two different environment representations i.e. model-based for dynamic elements and model-free fusion for static elements. Both representations have complementing advantages. On one hand, a model-based fusion, i.e. object tracking, can be designed to focus on dynamic objects reducing computational demand by avoiding tracking a static environment. On the other hand, model-free fusion can track the entire environment without the challenge to establish object models, avoiding measurement to an object association and clutter assessment.

The environment perception for RobustSENSE was tested in harsh winter weather conditions. Therefore, the developed environment modelling and fusion methods needed to be adapted to incorporate bad/winter weather data e.g. improved false positive detection ("ghost objects") induced through snow banks/walls or guard rails, improved tracking in low light and dark conditions and improved object spawning in feature-reduced environments. Moreover, to ensure the functionality under degradation, further testing and adaptation was done with degraded data resulting from performance reduced/degraded (iced over) sensors and the middleware was prepared for fail operational functionalities in order to compensate for (sub-) system outages and degraded operation.

Augmented generic sensor models

Contributing organisations of D3.3 (Package of generic sensor models for the sensor platform) generated a new concept of augmented generic sensor models to be used and demonstrated in different configurations of a simulation-based validation methodology (Figure 4.3).

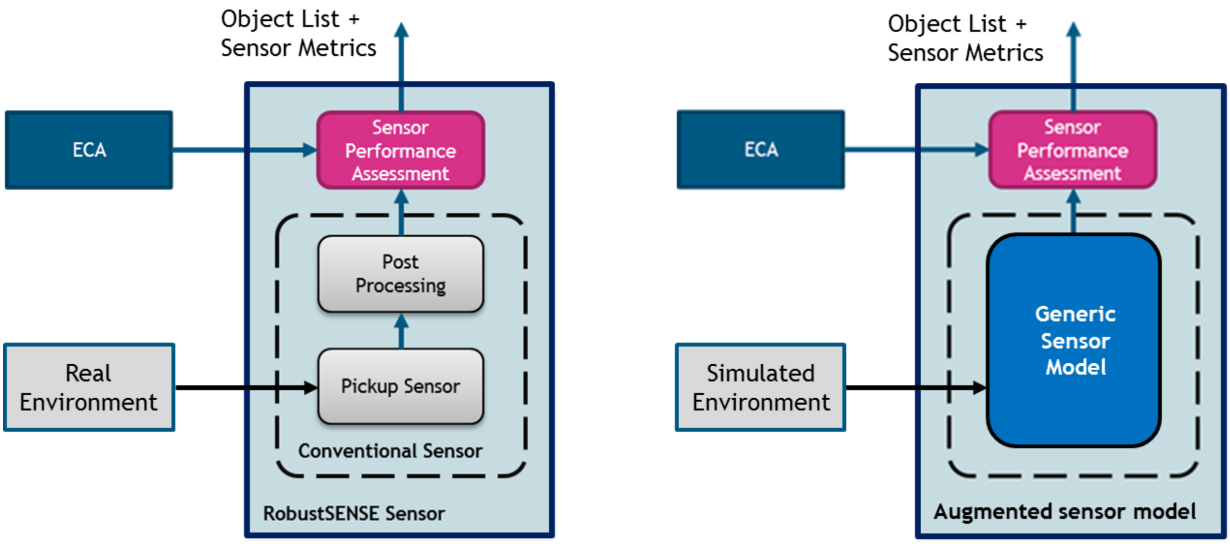

Figure 4.3: Augmented generic sensor model.

The notation of augmented sensor models was introduced to describe generic sensor models combined with low-level performance indication functions based on an environmental condition assessment (ECA) as shown in Figure 4.4 below.

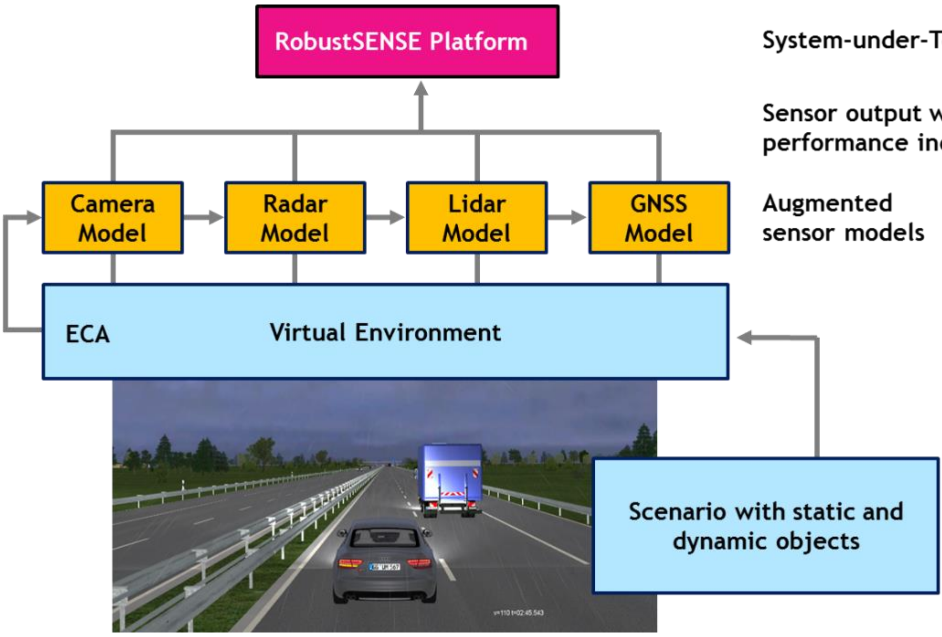

Figure 4.4: ECA & Real environment.

The developed framework of augmented generic sensor models resulted in a relative low effort for simulation of sensor behaviour in different environmental conditions and therefore enabled an effective validation of the high-level functions of the RobustSENSE architecture in simulation-based test environments.

4-layer LIDAR at 1550nm

The prepared functional study of a 1550-nm-LiDAR was based on a 1-layer LMS-151. The final RobustSENSE prototype is a 4-layer LiDAR based on a standard LD-MRS. With the new 1550-nm-laser-source both the transmitting as well as the receiving optics had to be adapted to the new wavelength. Therefore, new optical components for the transmitting and receiving path had been developed. Also the receiving array had to be coated with a filter designed for 1550 nm (Figure 4.5, Figure 4.6). The internal LiDAR firmware was adapted to the new needed output power control behaviour and the receiving characteristics caused by the new APD receiving array. All components had been combined into a working prototype which was reported in D3.2 (Final laser, optics and detector assembly integrated in the LiDAR prototype).

Figure 4.5: Transiving optics (left), coated receiving lenses (middle) and coated housing (right) for 1550 nm

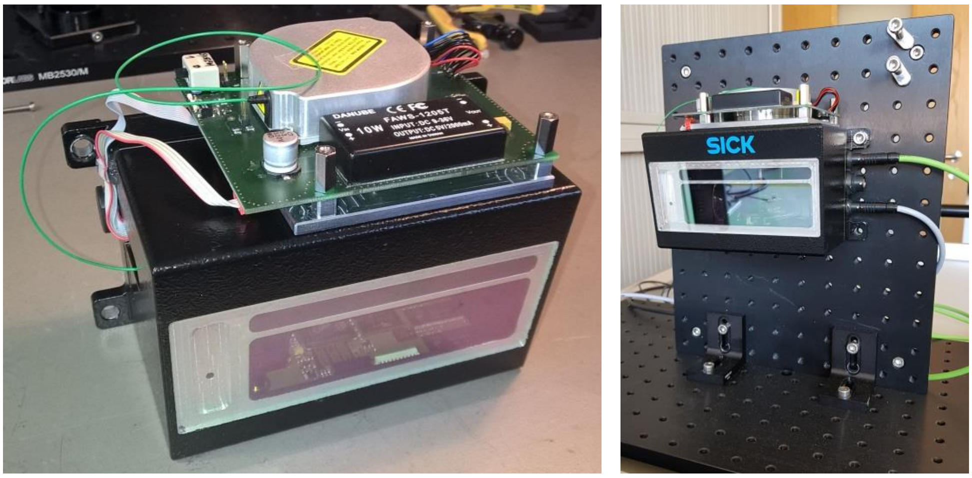

Figure 4.6: Prototype of a multi-layer LiDAR at 1550nm

The current prototype was consciously optimized to reach a maximum measuring distance. This was done by an optimized mechanical calibration of the laser source to the optical components and by an optimization of the receiving array to minimize noise influences. Additionally, a more IP67-proof housing was designed to use the LiDAR more easily in harsh weather conditions.

Measurements and signal evaluation

A polarimetric automotive radar measurement setup was successfully implemented to study clutter from road surfaces in variable weather conditions. The clutter was analysed for the different polarisations, and important trends were revealed (Figure 4.7). Measurements were carried out in dry and snowy conditions on public roads. The radar data was processed as post-measurements to identify the behaviour of the clutter for the different polarisations and to recognise trends which would signify important clues to the way various road surfaces ‘behave’ in varying weather conditions.

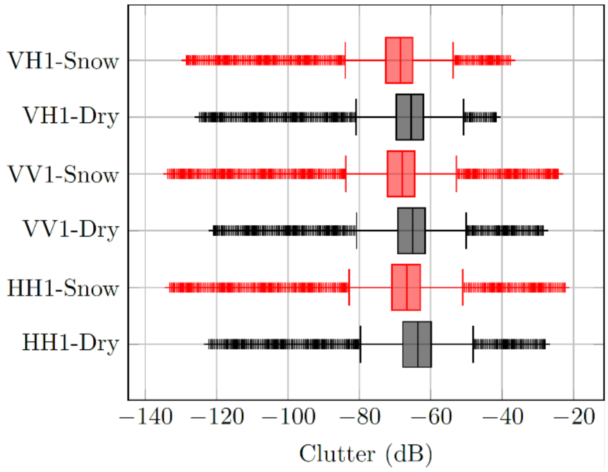

Figure 4.7: Clutter analysis by polarisation level.

The polarimetric behaviour of the clutter could be used to obtain additional information on the road surface. This information could then be passed onto the higher layers for the implementation of specific functions. They would act to mitigate or exploit the detected road surface conditions e.g. applying extra braking force to the wheels or giving less torque to the wheels to prevent them from spinning in given situations.

5 Situation understanding and planning (WP4)

5.1 Introduction

In WP4 the algorithms were developed to process the information about the environment provided by the various sensing components, to understand the current traffic situation and predict its potential evolution in the future. *A particular feature of these algorithms for scene understanding and situation prediction is the capability to infer classified relations and interactions among traffic participants and ongoing manoeuvres.* This information allows predicting the traffic scene at a higher abstraction level as compared to standard Bayesian filtering.

WP4 also developed the algorithms for behavioural planning for a given traffic situation and its anticipated evolution. They provide suitable abstract behaviour and concise driving trajectories. Similar to monitoring the performance of the various sensor components of the RobustSENSE sensor platform, also the performance of the various algorithms employed could be monitored. These consider in particular the uncertainties of perception and prediction by computing a metric to quantify the safety margin of the planned trajectories. Thus, the output of this work package did not only include a trajectory set that can be propagated to the controller. Additionally, information is provided on inherent safety and reliability levels crucial to safe driving.

5.2 Objectives

The overall objective of WP4 was to generate safe driving behaviour based on the perceived information and its inherent uncertainty.

This work package had the following goals:

- Analyse the information provided from the environment perception and its uncertainties to create a holistic scene description.
- Identify interactions among traffic participants that impact their future behaviour.
- Determine the possible evolution of the traffic situation with associated probability measures.
- Establish possible behaviours for the ego vehicle and assess their safety.
- Determine a suitable future trajectory with an associated safety metric and identify crucial postulations for these (such as rule compliance of selected traffic participants).

All modules were developed and tested in a simulation environment and were provided for vehicle integration and assessment in WP5.

5.3 Key achievements

Road understanding

Efforts in this WP were organized regarding the understanding of a road in two major directions and then, as a third activity using and training Convolutional Neural Networks (CNN) for the data collected.

1. **Road condition**: prediction of the friction relevant intermediate layer between the road surface and the tyre ahead of the ego-vehicle (Figure 5.1).

Figure 5.1: Road condition classification.

The sensor used was a mono camera system which was mounted behind the windshield (Figure 5.2).

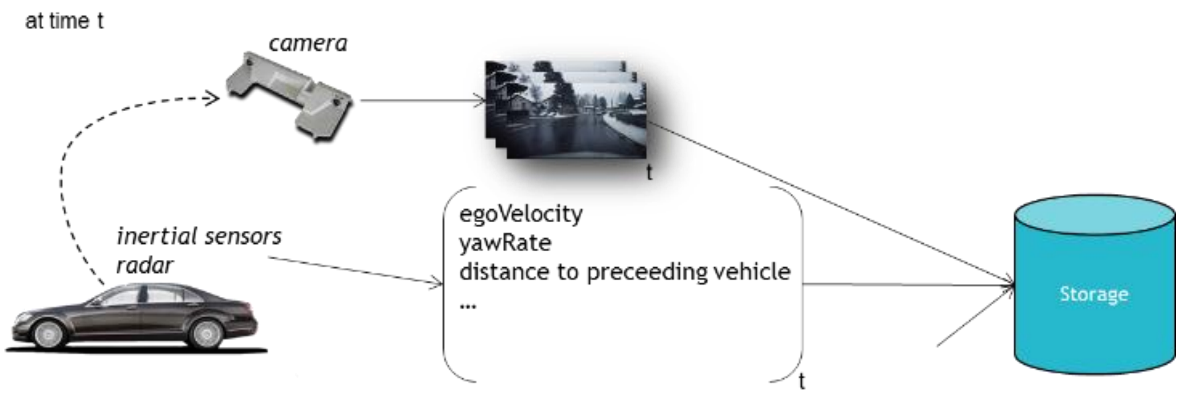

Figure 5.2: Data processing for road condition classification.

The database which is continually growing consists of a multitude of situations. The following figure gives some examples of snow covered road environments (Figure 5.3).

• • •

Figure 5.3: Examples of snow covered road environment for the classification of road surface.

The research and development was also carried out to enable more robust detection of water in addition to snow on the road surface.

2. **Road layout estimation**: prediction of the path of the lane ahead (e.g. when lane markings are not clearly visible – Figure 5.4)

Figure 5.4: Road layout estimation.

The path is represented by 4 points on the image that correspond to real world points in 10m, 15m, 20m and 25m distance in front of the vehicle, respectively. For the training process, these real world points were recorded during the test drives. In the next step they were projected into the image by a given camera projection. The x coordinates of the image points were normalized and computed mean free to use them as labels to learn by a CNN. Figure 5.5 below shows the labelling tool programmed to exclude certain scenarios and create the ground truth.

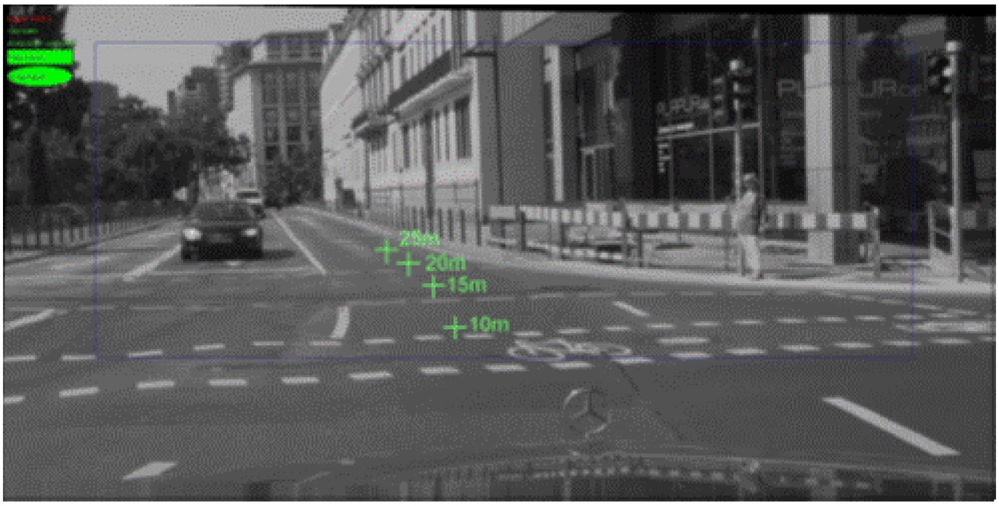

Figure 5.5: Labelling tool in use.

3. Development of a framework which allowed us to efficiently train Convolutional Neural Networks (CNN). One key challenge in these training tasks was to guarantee that the underlying data set is:
    - huge (lots of data),
    - well defined and
    - labelled.

Figure 5.6 below gives an overview of the integration and testing workflow:

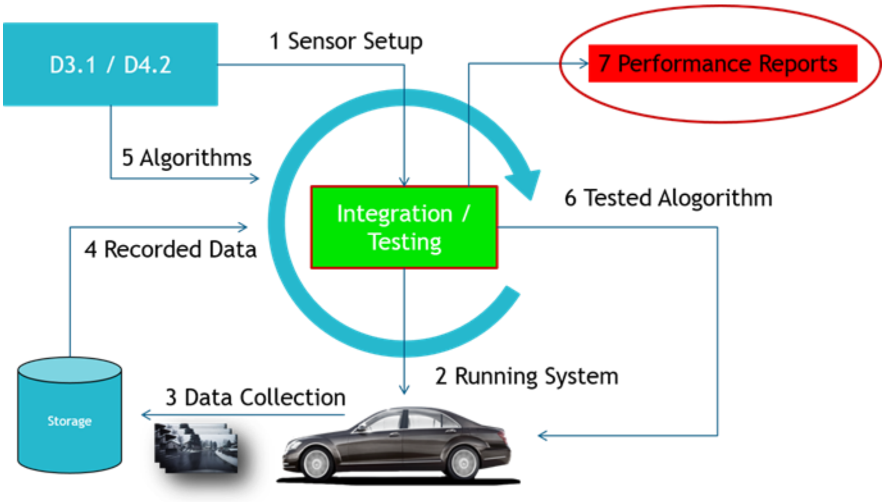

Figure 5.6: Testing workflow.

For an automated car it is of utmost importance to be able to handle also adverse weather conditions sometimes occurring spontaneously. It is already today listed as a requirement for future car generations.

Interaction detection and route prediction

For safe autonomous driving, interactions between traffic participants need to be detected and planned routes and trajectories predicted respecting the detected interactions. The system needs to know whether all traffic participants interact and react to each other (in a compliant or noncompliant behaviour) in a machine-readable way.

The key elements in the approach taken in RobustSENSE are the relation estimation and a filtering and prediction. Work on the relation estimation done as follows: For every object relations between possible routes, interactions and behaviours are estimated (Figure 5.7). Each behaviour matches a motion model. In the filtering and prediction steps we used Intelligent Driver Model-based motion models to estimate the current behaviour and predict future trajectories.

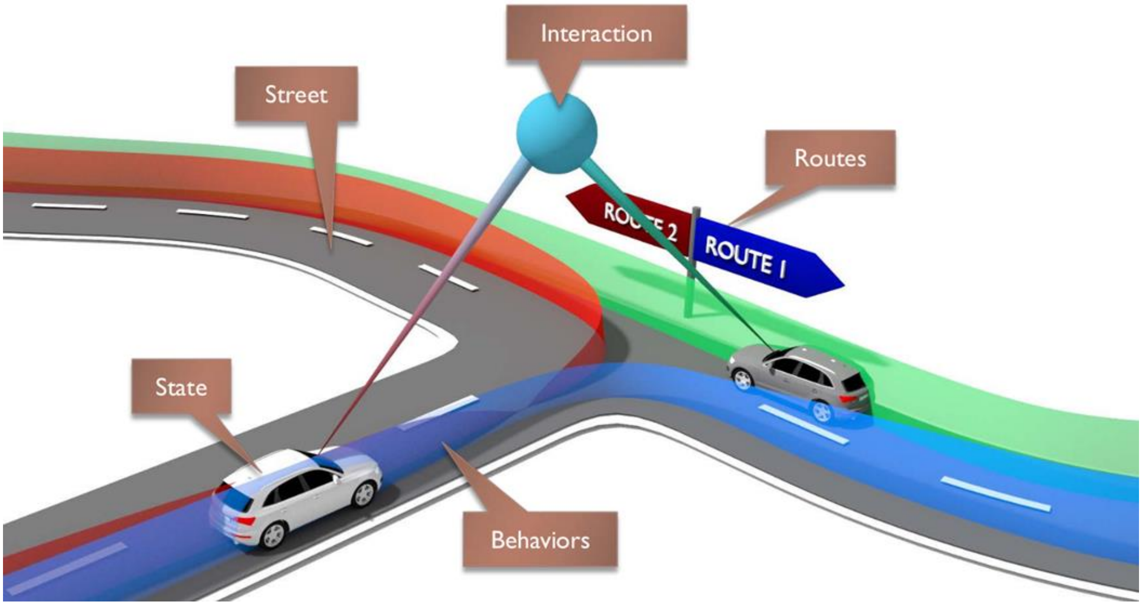

Figure 5.7: Relations between objects estimated by the scene understanding module.

The key achievements can be used to detect noncompliant behaviour. This allows the ego vehicle to handle harsh environment conditions including traffic participants that do not observe traffic rules. The basis for cooperative driving is always to consider the possibility of traffic participants not following traffic rules or safe behaviour overall. The planning algorithms that lead to cooperative automated vehicle behaviour need such a scene understanding.

Behaviour parameter estimation (incl. performance assessment)

The algorithm aims at the probabilistic estimation of behaviour describing parameters $\mathbf{x}$ of traffic participants enumerated by α. The parameters were used to model object acceleration depending on the relation to other objects in the current scene.

The considered scenario is illustrated in Figure 5.8. Vehicles with driving style parameters $\mathbf{x}^{(\alpha)}$ were tracked ahead of the ego vehicle. A third vehicle may be present, but is not detected. The influence of leading objects is modelled with relative kinematics in $\mathbf{u}^{(\alpha)}$.

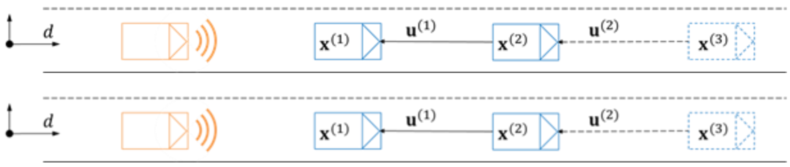

Figure 5.8: Vehicles with driving style parameters $\mathbf{x}^{(\alpha)}$.

Past research in the field of traffic flow modelling yielded parametric models of interacting driving scenarios. A well-studied model is the Intelligent Driver Model (IDM) describing a car-following scenario by means of ordinary differential equations. Among other models, the IDM parameters allow a physical interpretation. While the original use of the model is a simulation with fixed parameters, but the studies in RobustSENSE showed the applicability of the model to real-world data considering the model parameters as random variables. The decisive property for a real world application is that the estimated parameter distribution changes slowly as compared to a perception update.

Performance assessment relies on a probabilistic estimation. Filter divagation is a good indicator whether the model used and its assumptions suit the true situation.

The IDM targets car following scenarios including start- and stop-situations. The estimated parameters were later used for predicting start/stop-manoeuvres to support trajectory planning.

A Monte-Carlo based estimator was implemented, where particles approximate the PDF over behaviour parameters, vehicle dynamics and relations to the leading vehicle. Experiments with recorded trajectories were carried out to investigate the real-world applicability of the model in terms of parameter change rate and distribution modes i.e. unimodality.

To investigate the suitability of the model to the current situation, filter divergence was measured by the effective number of particles. For this, re-sampling was applied in every update step to achieve equal particle weights. The effective number of particles $\hat{N}$ is considered as the number of unique particles. We assume the model to be suitable if $\hat{N} > 0.5 \cdot$

N and define an performance indicator $\eta_{IDM} = \max\left(1, \frac{2\hat{N}}{N}\right)$. Typically, the performance indication will decrease if the model doesn't fit in the situation e.g. shortly before a crash.

The behaviour parameter estimation was used for trajectory prediction in car-following scenarios, where the main benefit can be seen in start/stop scenarios. The performance indicator will be used in the overall system monitoring to increase robustness.

Grid based model free prediction

As a complementing alternative to the object trajectory prediction, a model-free prediction was developed to predict future occupancy in a grid map. It was intentionally avoided to establish object hypothesis e.g. rotated rectangles, since a misinterpretation e.g. interpreting clutter as an object or missing objects, can lead to fatal accidents as has recently happened overseas. Instead, all regions occupied either by static or dynamic objects are fed to a long-term predictor.

A complex inner-city scene was recorded for multiple hours with multiple laser scanners. The sensors were fused in a dynamic occupancy grid map estimating dynamic states and occupancy in grid cells. A neural network was trained to predict occupancy of future time steps, given the current perception. The predicted occupancy compared to a simple particle prediction approach is illustrated in Figure 5.9. Model-free occupancy prediction: A dynamic occupancy grid map (left) was fed to a convolutional neural network to predict future occupancy at 0.5s, 1.0s and 1.5s. The output RGB images (three images right) illustrate the true occupancy in the red channel, learned prediction in the green channel and a simple particle prediction for comparison in the blue channel. An overlap results in mixed colours e.g. white at static regions.

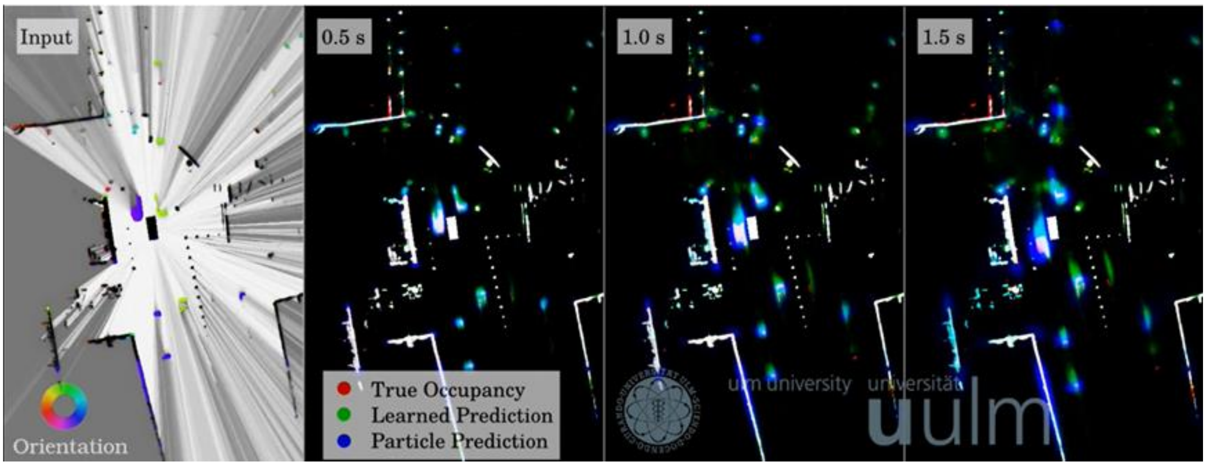

Figure 5.9: Model-free occupancy prediction.

The learned prediction was used as a redundant alternative to an engineered trajectory prediction.

Probabilistic behaviour planning based on semantic state

Different possible environment configurations resulting from harsh weather or uncertain driving behaviours were respected when building up constraints for trajectory planning. These constraints are represented as high level semantic manoeuvre chains, so called behaviour plans.

The probabilistic object information and route information were used to generate a semantic scene representation based on a special designed ontology. This scene representation was then used to build up a planning space for the ego vehicle. As the planning space has the structure of a directed graph, classic graph search algorithms like depth first search can be applied to generate semantic manoeuvre chains within the state space. Special adoptions and optimizations like heuristic-based search and integrated speed profile verification led to feasible semantic manoeuvre chains as results of the planning.

The created manoeuvre chains open up a new field of applications. While the application in the trajectory planning is straightforward, the condensed plan representation is also useful for the high level performance assessment and visualization of inner states for human operators and users.

Driver state dependent behaviour planning

A lateral and longitudinal trajectory planner based on Model Predictive Control (MPC) theory was developed and implemented.

In particular, a trajectory planning method was enlightened based on constrained optimizations that is able to generate a vehicle dynamically feasible, comfortable and customizable trajectory for highly automated vehicles at mid to high speed (Figure 5.10, Figure 5.11). The proposed algorithm aims at reducing computational cost of nonlinear optimization by decoupling longitudinal and lateral dynamics planning. This is achieved by using a sequential behavioural algorithm that combines a model-based scenario reconstruction with the planning of longitudinal dynamics manoeuvre and lateral dynamics planning if a lane change is considered.

The Trajectory Planning Model-based approach uses a series of Kalman filters in order to:

- Filter noisy signals (vehicle/obstacles accelerations, yaw rate, etc.).
- Reconstruct obstacle states in areas not covered by sensors.

- Reconstruct unavailable vehicle information (lateral vehicle speed).

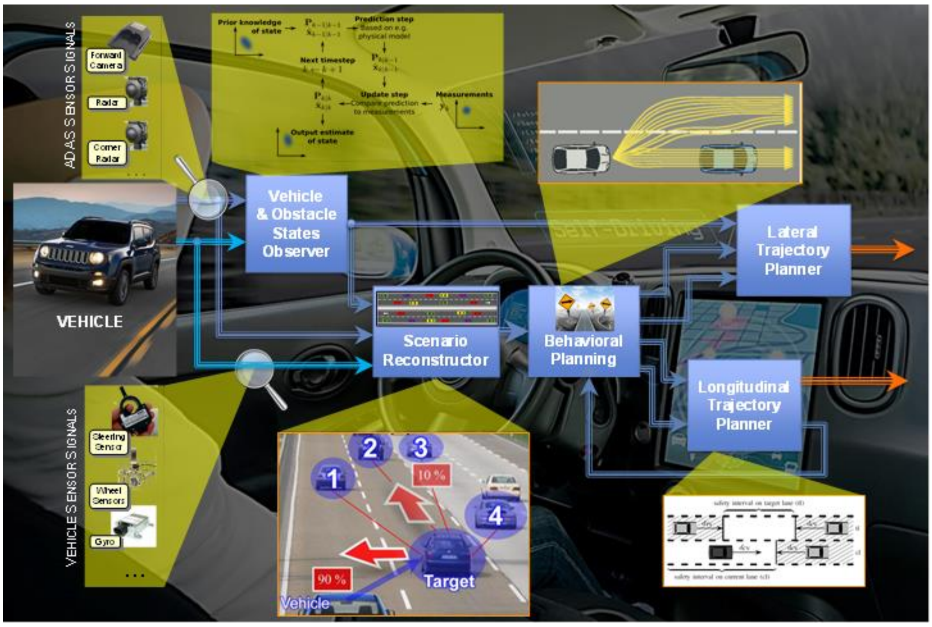

Figure 5.10: Block diagram for the trajectory planning model.

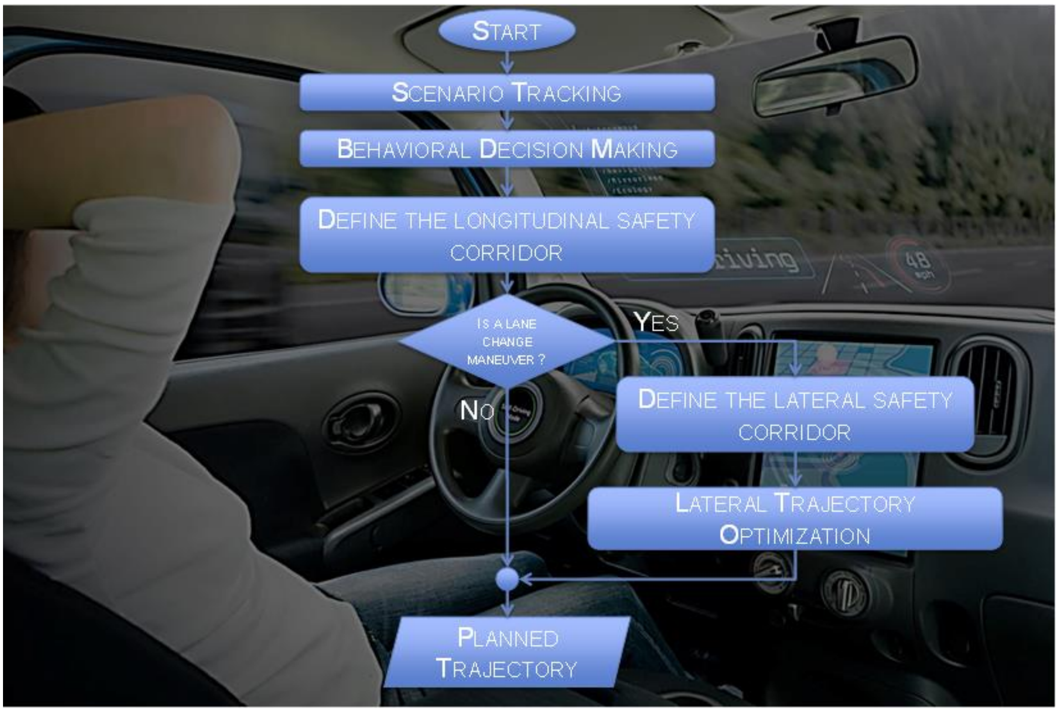

Figure 5.11: Flow-chart for the trajectory planning model.

Filtered and indirect measured signals are fundamental for the steps of ‘Scenario Reconstruction’ and ‘Behavioural Planning’ where the obstacle states are mainly used in this block: the filtered/reconstructed signals are the starting point to evaluate vehicle behaviour.

The host-vehicle motion was divided in a lateral and longitudinal direction. In particular, both lateral and longitudinal trajectory planners were based on the Model Predictive Control (MPC) theory. This approach uses a mathematical dynamic process model to predict a future value and to optimize the control performances. By means of the MPC it is possible to:

- Concurrently solve problems of obstacle avoidance, feasible trajectory selection and trajectory following. So trajectory planning and trajectory tracking are handled together.
- Guarantee theoretical closed loop stability obtained by a model based design.
- Integrate forward information resulting from traffic predictions or road geometry, obtaining smoother control actions and better control performances.
- Explicitly consider constraints on actuators and states/output values.

Thus, vehicle Longitudinal and Lateral dynamics are managed by means of two different trajectory planners where the longitudinal trajectory is planned before lateral planning. A real-time non-linear convex optimization problem is solved on a finite horizon based on an experimental validated linear model of dynamics to control/plan as well as a cost function of target variables and inputs to be minimized on a finite horizon.

This model takes into account also a series of constraints on system state variables useful to represent the ‘free corridor’ on the considered horizon as well as control targets as linear combination of system states to track the considered horizon.

Finally, the outputs of the Driver Monitoring System (DMS) can be used by the behavioural planning module as input, to change the selected action. So, for example, if the host-vehicle is approaching a slower obstacle ahead and all the conditions allow an overtaking manoeuvre, this can be delayed if the driver is classified as distracted (and executed when the driver is in the control loop again).

The next steps of development included:

- Improvements of low-level actuation control loops and actuators (e.g. tuning of algorithms to reduce the minimal fluctuations).
- Testing on more extensive and complex scenarios on real roads.

The first application of this approach (and of these algorithms) will be carried out on the Advanced Lane Support and Autonomous Emergency Avoidance (foreseen by FCA in 2021).

Safe trajectory generation considering traffic uncertainties

The trajectory planning module processes the environment information and calculates safe trajectories that are sent to the vehicle actuators and controllers for executing the driving directives. The uncertainties in the environment model accumulate up to this module and hence, the trajectory planner reliably deals with these and makes a trade-off between the driving targets and the level of criticality. It considers the actions that the automated vehicle can execute while continuously evaluating its performance. In this way, considering the operational status of the system, safe and at the same time not over-conservative trajectories are planned.

For safe motion planning hypotheses for hypothetic vehicles at the borders of visibility range were utilized (Figure 5.12). The hypotheses correspond to worst case scenarios from the point of the automated vehicle. The automated vehicle plans trajectories so that the vehicle can react to the hypothesis in case the hypothetic vehicle really exists. In this way, safe driving at blind corners is achieved. By further taking the braking distance of another vehicle into account, incompliant behaviours of others can be compensated (2).

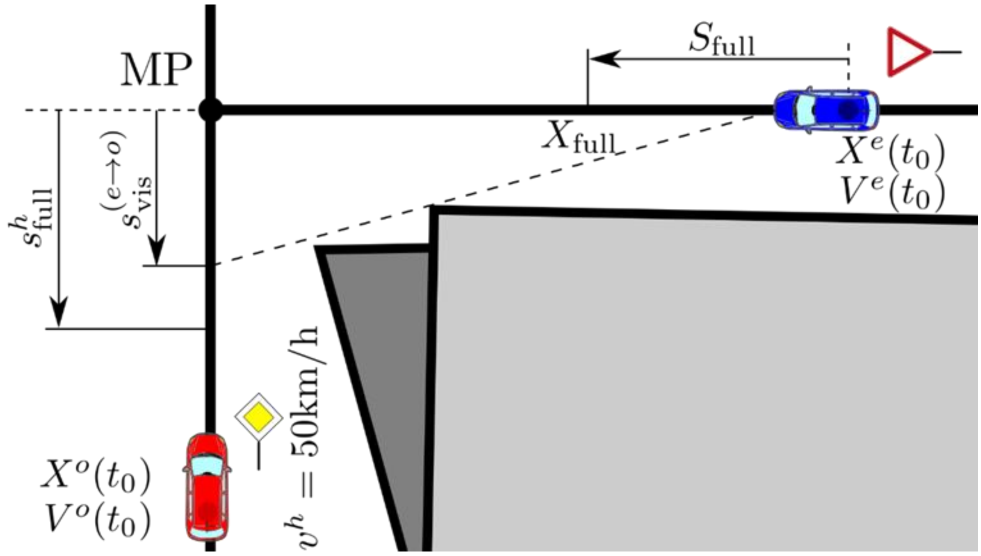

Figure 5.12: An automated vehicle, shown in blue approaches an intersection. It considers the hypothesis that there might be a vehicle approaching the intersection with allowed speed limit.

The trajectory planning approach developed in RobustSENSE also considers the uncertainties in localization and perception. The perception errors are propagated and dealt with in the trajectory planner (2).

In Figure 5.13 below right after the visible range of the ego vehicle, again shown in blue, there are vehicles stopped. The localization is uncertain. Hence, the stop position of the ego vehicle itself is uncertain as well. Given a confidence interval, the braking distance is not allowed to deviate from that interval. The trajectory planner considers this during its operation.

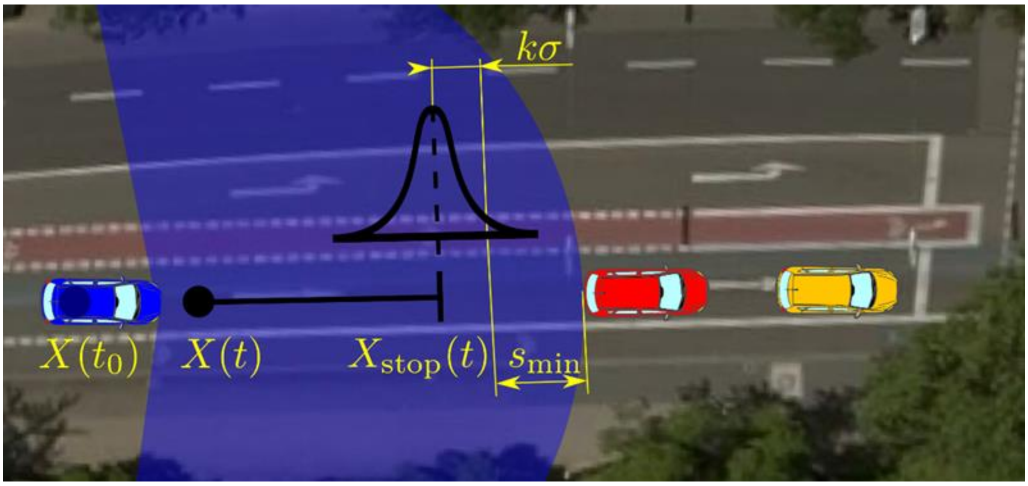

Figure 5.13: Right after the visible range of the ego vehicle

RobustSENSE trajectory planning further evaluates its performance during its operation. It considers the quality and criticality of the resulting trajectory and the operational performance of the planner itself (Figure 5.14) (3).

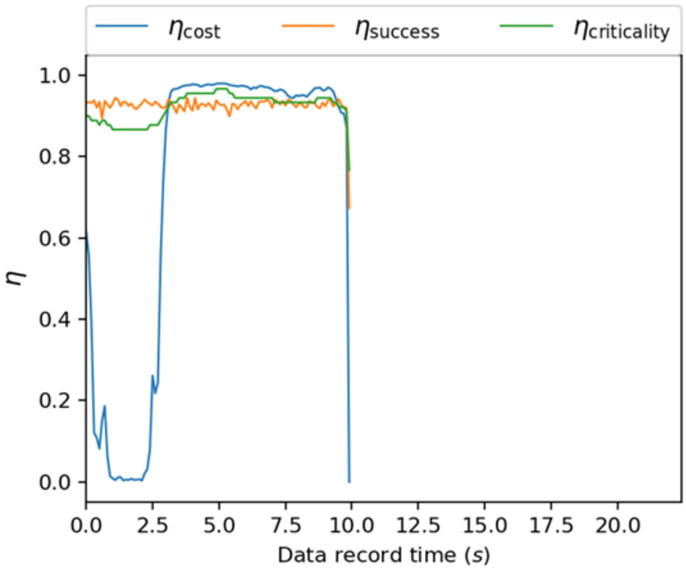

Figure 5.14: The metrics reflecting the operational performance of the planner.

State of the art trajectory planners typically do not consider the reactive manoeuvres that the vehicle could execute for the worst case evolution of the current scene. Furthermore, they do not monitor their own performance. By combining both, the key requirements in RobustSENSE trajectory planning, *safe and reliable driving* were achieved, and it lays the foundation for future trajectory planning development.

6 Integration and validation (WP5)

6.1 Introduction

In WP5 the various hardware and software components of the RobustSENSE platform were put together into a working prototype system. Firstly, its proper functioning along the specifications set up in WP2 was assessed under laboratory conditions. Once proper functioning was confirmed, the sensor platform was integrated in the demonstration vehicles of the partners in order to use the RobustSENSE platform to enhance the functional range of these vehicles. Apart from the work needed to implement the sensor platform in the vehicles, this task also included an adaptation and partial new development of the algorithms for vehicle control. Functional tests completed the vehicle integration.

Last but not least, the completed vehicles were extensively tested on real roads and simulation environments in order to validate the sensor platform and the functional enhancements provided for driver assistance systems. Particular care was taken to cover all relevant weather and light conditions through testing in Nordic winter and under reproducible conditions in a fog chamber.

6.2 Objectives

The main objective of WP5 was to perform the integration and global testing of the RobustSENSE perception platform in prototype vehicles to validate the enhanced level of robustness.

This objective was reached through the following steps:

- Develop a system performance assessment module able to collect the performance measurements from the whole system.
- Integrate all resulting modules in a global sensor perception platform.
- Integrate the perception platform in a/several vehicle prototype/s.
- Develop a suitable validation methodology considering sensor robustness level for automotive systems with a high level of automation.
- Perform RobustSENSE validation in the laboratory and in realistic outdoors test sites.

To construct the prototypes from the modified existing ones, the electronics and interfaces for the use of the computational platforms were integrated. Thereafter, laboratory and environmental testing of the integrated systems were carried out, and the integrated systems were assembled in the test vehicles. The validation was specified and conducted in the realistic test sites.

The main result were seven working demonstrator vehicles together with validation results and conclusions to be drawn in WP6.

6.3 Key achievements

An integrated multi-sensor perception system

The integration of the new LiDAR to the Marilyn automated vehicle for evaluating whether the 1550 nm improved performance in foggy conditions. The two standard SICK LD-MRS 4-layer and two 1-layer LiDARs were implemented to balance the performance of the LiDAR sub-system in foggy conditions.

A Volkswagen Golf Variant, depicted in Figure 6.1, served as the main demonstrator vehicle testbed for the RobustSENSE system and provided and integrated long-range radars (LRR), medium-range radars (MRR), and a stereo video camera (SVC).

Figure 6.1: The prototype vehicle on a test track.

The prototype vehicle was equipped with Sensors, actuators and additional vehicle specific parts such as measurement equipment and gateways. The work consisted of software development and an integration of the LiDARs into the vehicle DDS interfaces (Figure 6.2).

Figure 6.2: Vehicle DDS interface.

The RobustSENSE compliant fusion architecture was integrated in the overall system. To ensure the reliability of the input data on the fusion layer, the sensor level validation of the mounting position and pose information was performed. Degradation was achieved by switching off individual sensors one by one. The integration and evaluation focused on the verification of RobustSENSE architecture for robust environmental sensing in the presence of harsh winter weather and light conditions.

Visibility in fog is improved at least by a factor of 2.5 compared to standard lidars. Thus, e.g. in fog and snow, snowbanks are automatically detected much earlier, which in turn allows automatic driving in winter. The penetration through fog is also improved followed by a better pedestrian detection. The penetration through fog is also improved followed by a better pedestrian detection.

A RobustSENSE validation methodology

The fog chamber measurements conducted in WP3 were reported for different spectral responses. The validation of the real 1550 nm LIDAR prototype was carried out in the end of the project.

Software was developed for reading LiDARs and estimating sensor performance. The software takes point cloud input and optimises the parameters. The snow error removal filter was also developed.

The specified validation methodology was demonstrated on the implemented RobustSENSE platform of a prototype vehicle as shown in Figure 6.3 below.

Figure 6.3: The prototype vehicle.

The testbed was set up AVL for tests of automated driving in harsh weather conditions. The laboratory environment allows the simulation of adverse weather testing independent of actual weather conditions. The test vehicle for RobustSENSE on a vehicular testbed is shown in Figure 6.4.

Figure 6.4: RobustSENSE vehicular testbed.

As RobustSENSE use cases base on a harsh winter weather conditions, the main test was conducted at Bosch's winter test center in Arjeplog, Sweden. The test aimed at analysing the effects of a sensor unavailability on the overall performance of the fusion system. Individual sensors were switched off, and the influence of the respective sensor degradation on the fusion performance was analysed.

The fog chamber tests carried out in WP3 has been used as a seed to further elaborate the new LiDAR which bases on old electronics but uses new optical components and laser source. The bandwidth analysis forms the basics for developing the performance assessment module for the automated car "Marilyn". The reference sensors have been implemented for evaluating performance improvements. Snow removal filter technique was developed for removing the noise from the LiDAR data caused by turbulent drifting snow (Figure 6.5).

Figure 6.5: Filtering technique.

The developed augmented generic sensor models were used to interface a simulation platform with the RobustSENSE platform inside the vehicle as shown below (Figure 6.6).

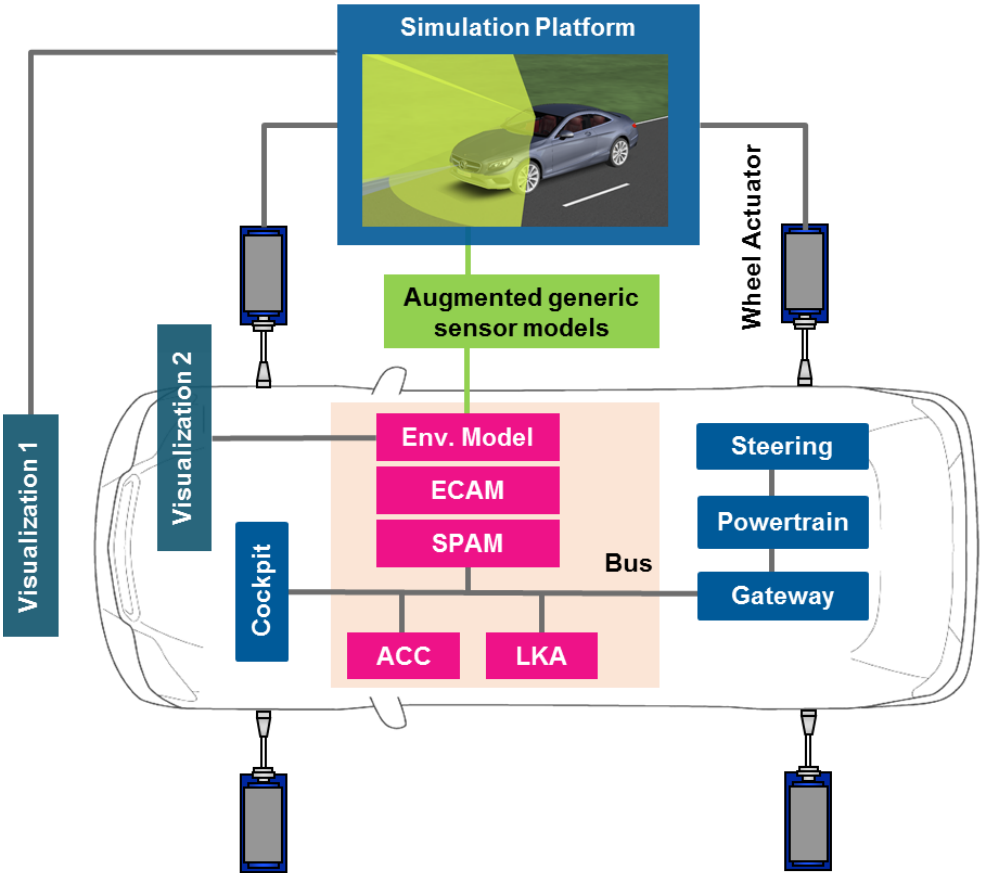

Figure 6.6: Interfacing a simulation platform with the RobustSENSE platform inside the vehicle.

As a use-case for higher-level functions a combined ACC (Adaptive Cruise Control) and LKA (Lane Keeping Assistant) was selected and implemented in the RobustSENSE platform together with an ECA and SPAM module. Different virtual scenarios were tested on a driving simulator and vehicle test bed was used to validate the performance of the RobustSENSE platform in different environment conditions as shown below (Figure 6.7).

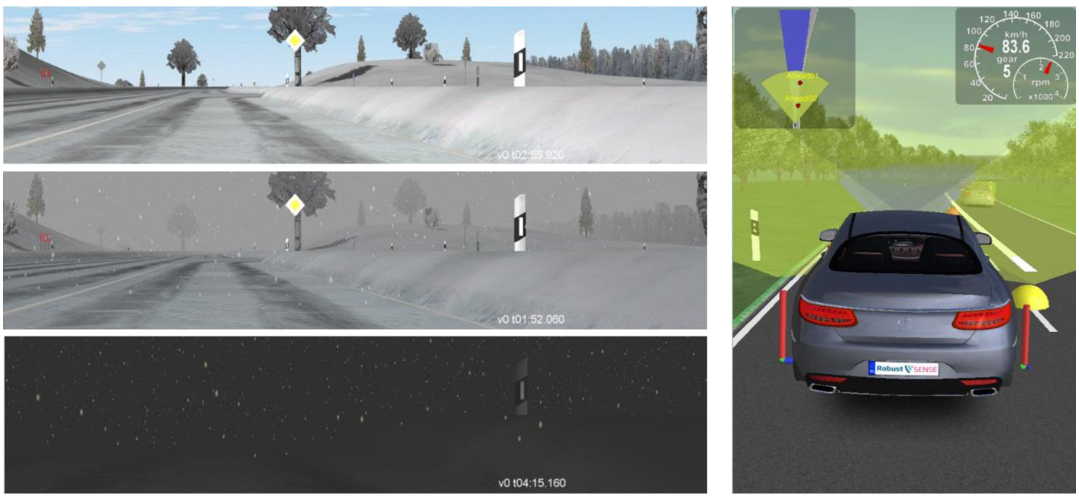

Figure 6.7: RobustSENSE test facilities.

The scenarios have been applied directly to the vehicle with the AVL DrivingCube™. The pictures below shows the setup of the testbed (Figure 6.8).

Figure 6.8: Setup of the testbed.

The validation results were used to tune the parameters and improve the performance of the automated driving functions in foggy conditions. The performance assessment module was developed to optimise three different LiDAR principles: 1) 905 nm, 4 layers, 2) 905 nm, 1 layer and 3) 1550 nm, 1 layer when the visibility degrades. The snow removal filter patenting process has been started, and the module will be commercially utilised to improve LiDAR performance in snowy conditions.

The specified validation methodology from WP2 and the lessons learned from the prototypical implementation and demonstration in WP5 will be used as an asset for an efficient validation and even a possible homologation of safety critical driving functions in adverse weather conditions in the future.

The system validation was done mainly based on an expert opinion. A quantitative measure for verifying and validating the performance of the fusion system needs to be provided for successful release of the function. Further work should be invested in the fusion system validation.

Bayesian fusion of performance assessments

Several performance measures are fused into an overall system performance measure. Single performance values that are not significant on their own are combined to derive a clear statement. It was shown that problems that were not able to be detected by probabilistic processing alone can now be detected by means of an overall system performance assessment.

An exemplary implementation of a Bayesian Network approach was integrated using components from all three layers of the system architecture. The idea of the Bayesian Network approach is to factorize the big, hardly modelled conditional dependency of several performance metrics into challenges with less complexity. Per module performance assessment metrics are discretized into discrete qualitative values that are brought into relation in the discrete Bayesian network. Figure 6.9 shows a Bayesian network of an exemplary ghost object scenario.

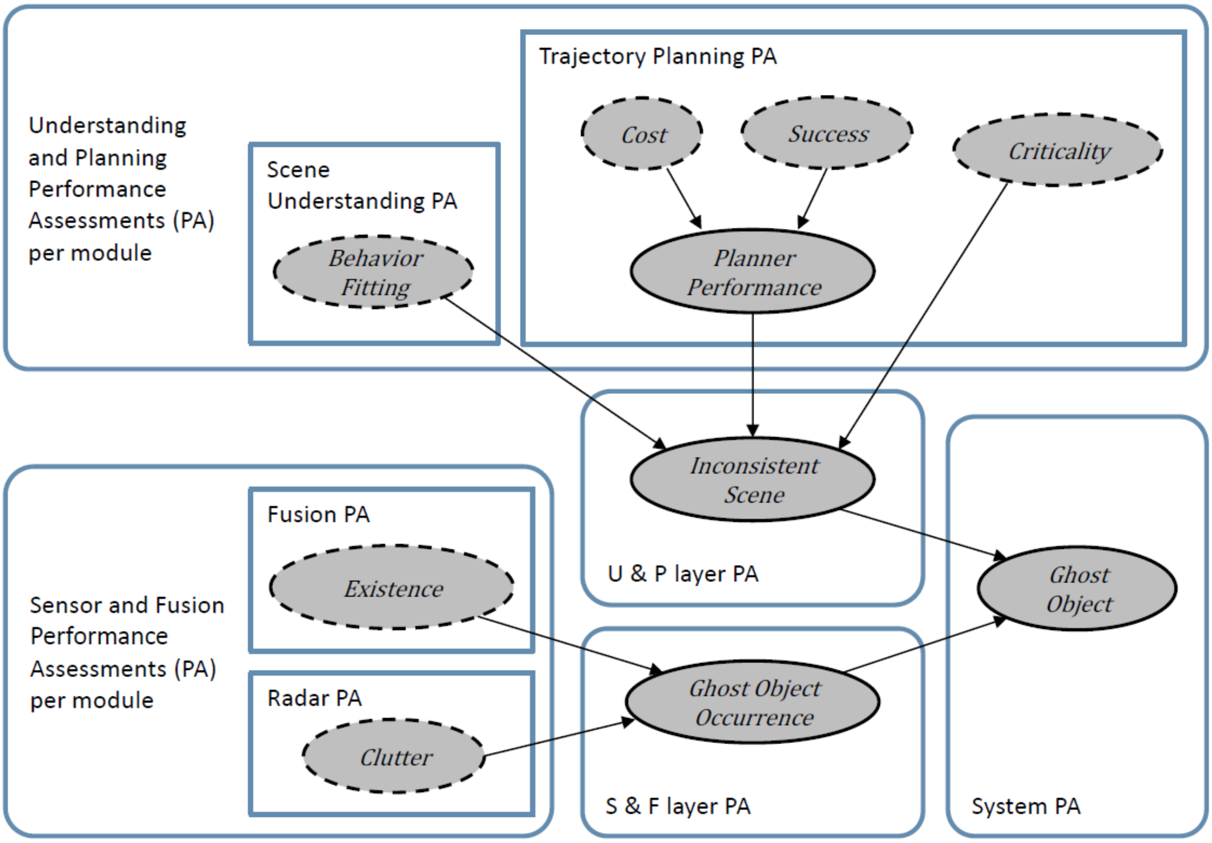

Figure 6.9: Performance Assessment for the ghost object scenario as a discrete Bayesian Network.

The Bayesian Approach is the first idea of realizing such a fusion of several performance measures in a probabilistic way. It lays the foundation for future research including the integration of Dempster Shafer Evidence Theory to detect and handle inconsistencies among these measures.

7 Future exploitation

7.1 RobustSENSE exploitation approach

One of the key objectives within the project work package 6 was to investigate the business potential of the RobustSENSE system and develop exploitation perspectives for the European automotive, electronics and supplier industry. Different applications of the system in the automotive sector but also in other fields related to automation have been elaborated and market requirements have been evaluated.

A holistic and integrated methodological approach was developed to analyse the exploitation perspectives, including four main building blocks: 1) partner specific exploitation plans, 2) online expert survey, 3) exploitation workshop (D6.3) and 4) final exploitation report (D6.5). The deliverable D6.5 Exploitation Plan outlines the major outcomes of all the four building blocks and provides a deeper outlook on the deployment perspectives of the technological solutions developed. It also includes partners' specific exploitation plans.

This chapter summarises the main findings concerning general exploitation perspectives and business potential of the RobustSENSE technologies.

7.2 Exploitation perspectives of the project results

The project identified nine categories of major exploitation fields for the RobustSENSE results which are captured in the Figure 7.1 below

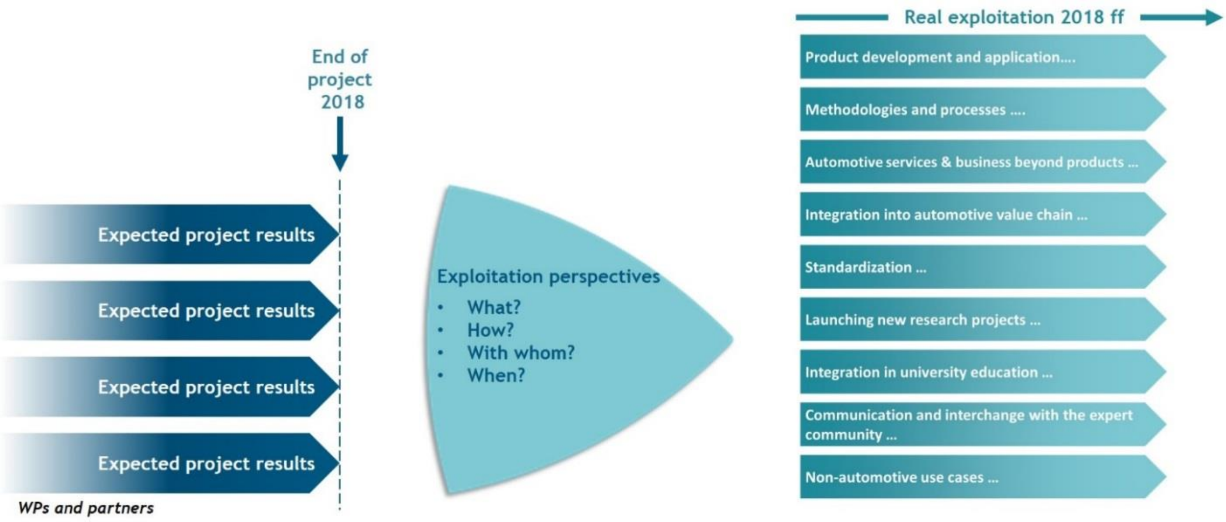

Figure 7.1: Exploitation perspectives

Four of the fields were analysed in more detail, seeing as major potential fields where project results could be further exploited.

In the area of *product development and application* the development of a new automotive LiDAR is promising and the time frame for market implementation is seen within the next five years. Another important topic is the upgrade of regular sensors including output self-assessment information and ECA input acceptance. In order to achieve this objective joint effort of all sensor manufacturers and other stakeholder groups is necessary in terms of working groups and standardization bodies to determine interfaces, data formats etc.

Concerning *launching new research projects* and *integration into university education* a variety of new research topics were identified. In order to address the topics the partners indicated the initiation of new research projects, customer assignments (from OEMs, Tier1 suppliers) or the setup of new partnerships to combine complementary resources and push the development. An early integration of research project results into university education to train young talents, spin-offs or transfer workshops with the wider expert community are further means to drive the development.

In addition to the technology-based exploitation issues exploiting *methodological and process-related knowledge* gained in RobustSENSE was discussed. Notably the academic partners will exploit new knowledge on failure tolerant algorithms and performance self-assessment of systems making the RobustSENSE concept a fundamental basis for future robust AD architectures. New methods will be made available on how to guarantee machine vision performance in practice. First insights into interactions between the platform's modularity approach – using different sensors from different manufacturers – and the various fusion levels will be deployed by system integrators and manufacturers in further R&D projects.

Integration into automotive value chain is a clear focus of the RobustSENSE as the project is developing hard- and software technologies for ADF. The developed technologies will mainly find their future exploitation in automotive applications, like passenger cars, vans, trucks and busses. But exploitation is not limited to automotive fields. Some of the project partners already named in their exploitation plans *non-automotive fields*. There are a lot of possible applications beyond automotive, where objects or vehicles have to move in bad weather and sight conditions. Improved sensing capabilities, elaborated in RobustSENSE, can support automation of movements and non-automated safety improvements, as well as a higher safety and security by better surveillance of areas affected by bad weather or sight conditions. The RobustSENSE exploitation workshop was used as a mean to open up the partners' exploitation focus on non-automotive applications. The outcomes of the workshop were analysed and clustered as shown in the Figure 7.2 below.

Transportation	Robots	Agriculture
Use cases in non-automotive transportation fields like aviation or shipping	Use of robots in very different areas like factories, households, cleaning or education	Using sensor technologies in agricultural automation and in food quality control
Sorting & Exploring	**Unstaffed Risky Missions**	**Entertainment**
Usage of high resolution sensors in sorting objects or trace recognition	Substituting some hazardous human operations in firefighting or movie stunts	Application in leisure time activities, e.g. in playgrounds or in specific types of tourism

Figure 7.2: Clusters - Application fields for non-automotive use cases.

The exploitation perspectives of the sensor platform were also inquired through an online expert survey with project internal and external experts. The survey provides insights from various fields of expertise, covering not only technical but also market related aspects. The main results can be summarised as following:

- The RobustSENSE sensor platform is seen as a really necessary and promising approach to ensure ADF under harsh weather conditions.
- There are still relevant concerns about the required technical performance and the associated cost of the components and the whole system.
- The willingness of OEMs and suppliers to cooperate in that field (to develop open and standardized solutions) is crucial for a broad application of the RobustSENSE sensor platform in the automotive sector.
- A success in the automotive sector can open more business opportunities for the RobustSENSE sensor platform in various non-automotive application fields.

7.3 Business potential of the sensor platform

The business potential of the RobustSENSE sensor platform in the automotive sector is promising and use cases here are easy to describe: Every car ready for automated drive on level 3 or higher needs the ability to drive under harsh weather conditions. A suddenly appearing fogbank or drifting snow from a car or a truck running ahead, causing blindness of e.g. an optical sensor, should not necessarily lead to an emergency break of the automated driving vehicle. In the consequence, every level 3+ vehicle has to be equipped with a robust sensing function, be it based on the RobustSENSE sensor platform or on any other technology.

Nevertheless, it is difficult to make detailed analysis of potential market shares as many factors remain still uncertain. For example the estimations on the number of the level 3+ cars on the market by 2030 varies. The span of projections reflects the big uncertainties related to the expected development. Precautious estimations expect about 17.5 million level3+ car sales in 2030, more optimistic institutes expect up to 40 million level 3+ car sales. McKinsey is framing these estimations with two very different scenarios, where sales figures vary strongly between 2 million vehicles up to 63 million vehicles. Assuming total global sales of about 100 to 120 million cars in 2030, level 3+ cars are expected to have a share between 2% and 55% of the total global market. Aside from the McKinsey low penetration scenario, that are really relevant numbers and show in total a relevant business potential for the corresponding technical solutions.

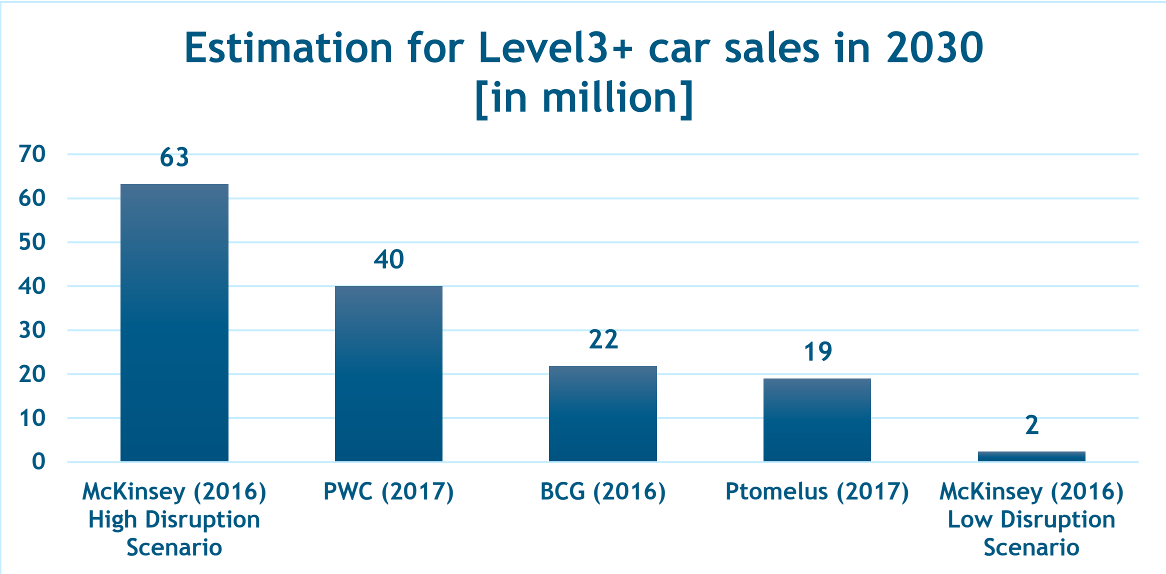

Figure 7.3: Overview on published estimations for level 3+ cars in 2030.

(Own graph, based on McKinsey, 2016; PWC, 2017, BCG, 2016 and Ptomelus, 2017)

Besides, the RobustSENSE sensor platform will not be the only future technical solution for handling harsh weather conditions. A lot of companies are working on this issue, also outside Europe. It can be said that the competitive starting point for the European automotive industry is quite good, but the efforts need to be continued and intensified to strengthen the research and development activities in order to remain the leading role in the future.

Especially during the next years, the competition will likely get harder as all automotive manufacturers, big suppliers, and IT companies will increase their R&D activities. This situation will probably lead into a consolidation phase, where cooperation and merger & acquisitions take place to bundle power and budgets, and to push standardization.

As said, the future business potential for a RobustSENSE sensor platform is really relevant in the automotive business but can be driven additionally by non-automotive application fields. The system has the potential for creating cross-industry innovation from automotive industry to other sectors and vice versa. Nevertheless, the willingness of OEMs to cooperate with suppliers and SMEs from other industries seems to be crucial for a broad application of the RobustSENSE sensor platform and its components.

8 Conclusions

8.1 Lessons learnt

This section presents the major lessons learnt in the project which turned out at different project stages.

8.1.1 Project planning

- Provide an overview on the various SW modules and their interfaces. Show feasibility by integrating and demonstrating the complete SW architecture in one of the test vehicles.
- Existing and planned TRL levels need to be communicated thoroughly.
- Software interfaces towards actuators need to be considered as part of the architecture.
- Employ metrics to determine whether a test case succeeds or fails.
- Provide an adequate quantifiable baseline and clear evaluation criteria regarding the sensing robustness in harsh environmental conditions.

8.1.2 Project management

- Develop and implement a proper method to monitor the technical progress regularly and ask for input from all consortium partners.
- Risk management activities should be technically oriented, with involvement of all partners on a more regular basis.
- Establish an integration plan early in the project, including early prototypes and demonstrators. Provide pre-prototypes in reviews with the funding authorities.

8.2 Project results

RobustSENSE designed, developed, and evaluated a sensing system to cope with real world requirements under all environmental conditions. The RobustSENSE system introduced reliable, secure and trustable sensors and software by implementing self-diagnosis, adaptation and robustness.

The four main pillars developed in the project were presented in the previous chapters, and a brief summary of the corresponding results is given below.

<u>Requirements and specification</u>

- Development of an overall system architecture including component and interface definitions.

- Definition of additional functional and non-functional components responsible for performance assessment.
- Metrics specification and validation plans development for each component.

Environment perception

- Development of first prototype scanner with 1550nm wavelength.
- Setup of a fog chamber for LiDAR validation.
- Definition of quality metrics and concept for the camera optics cleaning system.

Situation understanding and planning

- Develop CNN system concept
- Software design for algorithm performance monitoring.
- Modification of existing LiDAR for easy interchange of their laser and sensor parts.

Integration and validation

- Development of the system performance assessment module.
- Definition of the main inputs, levels of degradation for each sensor and the architecture of this module Demonstration and exploitation.
- Test case description and validation tools definition.

8.3 Success Stories

Despite the technical and organisational challenges that were overcome in the course of the project, there emerged some success stories that are worth mentioning herein.

Project Animation

Communication and dissemination of the foreground are always central topics in projects like RobustSENSE. Since these projects usually take place in a pre-competitive setting the content and information is almost always of a very special interest, meaning that usually only specialists and experts are reachable for these efforts. In RobustSENSE we managed to develop a project animation that addresses the general public explaining the approach and aim as well as the main results of the project in an easy to understand manner thus making it even possible for kids to understand what the project did. See www.youtube.com/watch?v=ol4F-H1RlJM to watch the whole animation film.

Setting a potential world record

RobustSENSE partner VTT showcased some RobustSENSE aspects in January 2018 at the Aurora Summit in Olos, Finland potentially setting a world record for autonomously driving in snow when the robotcar “Martti” reached 40 km/h. See www.youtube.com/watch?v=C3GgJoVTHSU for a video of this ride.

The press release by VTT accompanying the Aurora Summit resulted in global press coverage picking up on the topic of autonomous driving in snow and other adverse weather conditions ranging from the Americas to India and Australia. This clearly shows how important this research is considered.

The robot car “Martti” at the Aurora Summit, January 2018

Final Event

In May 2018 the project held its concluding Final Event in Ulm, Germany. In this one-day event six driving demonstrations showing various aspects of the RobustSENSE sensor platform were presented, a conference with presentations about the key features and results and an extensive exhibition with posters, videos, a live-stream, hardware exhibits and a workshop took place. Over 80 guests attended this event, 25 of which from companies and institutions outside of the RobustSENSE consortium. Again, for such a relatively small and very special interest project, this is an impressive reach.

References

1. **international, SAE.** https://www.sae.org/standards/content/j3016_201609/. [Online]

2. **Ömer Sahin Tas, Christoph Stiller.** Limited Visibility and Uncertainty Aware Motion Planning for Automated Driving, in proceedings of IEEE Intelligent Vehicle Symposium, Chang Shu, China, 2018.

3. **Ömer Sahin Tas, Stefan Hörmann, Bernd Schäufele, Florian Kuhnt.** Automated Vehicle System Architecture with Performance Assessment, in proceedings of IEEE Intelligent Transportation Systems Conference, Yokohama, Japan, 2017.

4. **Kuhnt, F., Kohlhaas, R., Schamm, T., & Zöllner, J. M. (2015).** Towards a Unified Traffic Situation Estimation Model – Street-dependent Behaviour and Motion Models –. In 18th International Conference on Information Fusion (Fusion) (pp. 1223–1229).

5. **Kuhnt, F., Schulz, J., Schamm, T., & Zöllner, J. M. (2016).** Understanding Interactions between Traffic Participants based on Learned Behaviors. In IEEE Intelligent Vehicles Symposium (IV).

List of abbreviations and acronyms

Abbreviation	Meaning
ACC	Adaptive cruise Control
APD	Avalanche photodiodes
AV	Automated vehicle
AVL DrivingCube	Virtual development and validation environment for intelligent vehicles
Clutter	Unwanted echoes in electronic systems, particularly in reference to radars
CNN	Convolutional Neural Network
DDS	Data Distribution Service
ECA	Environment Condition Assessment
ECSEL	Electronic Components and Systems for European Leadership
ECSEL JU	Electronic Components and Systems for European Leadership Joint Undertaking
Ego-vehicle	Reference vehicle in relation to which other traffic participants' movements are measured; or traffic environment's objects; 'test vehicle'
FCA	FIAT Chrysler Automobiles
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
H2020	Horizon 2020
IDM	Intelligent Driver Model
IP67	Most environmentally sealed housing is rated 'IP67'
LiDAR	Light detection and ranging
LKA	Lane Keeping Assistant
LRR	Long-range radar
MPC	Model Predictive Control (theory)
MRR	Medium-range radar
OEM	Original equipment manufacturer
PDF	Probability density Function
RGB- image	Data array that defines red, green, and blue colour components for each individual pixel
SAE	Society of Automotive Engineers
SPAM	Smart Power Assisted Module
SVC	Stereo video camera
SWIR	Short-Wave Infrared
TRL	Technology Readiness Level
V2X	Vehicle to X
WBS	Work Breakdown Structure
WP	Work package