



Automotive Intelligence for Connected Shared Mobility

| Deliverable | <i>Report on technical requirements and specifications for AI-enabled perception and sensors fusion systems and platforms and the definition of SC6 use cases.</i> | | |
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1 Executive/ Publishable summary

This document is intended to give an overview of “**Requirements and specifications for AI-enabled perception and sensors fusion systems and platforms**” collected from all partners participating in task T1.6 of AI4CSM Work Package 1 (WP1) for Supply Chain 6 (SC6).

Task T1.6 results are fundamental to SC6, which targets to provide five demonstrators:

- SCD 6.1: **Perception and vehicle intelligence platform** (lead: NXPN)
- SCD 6.2: **Neuromorphic sensor fusion** (lead: IMEC)
- SCD 6.3: **Affordable AI-enabled perception** (lead: SINTEF)
- SCD 6.4: **Localization and 3D mapping** (lead: BUT) and
- SCD 6.5: **3D Time of Flight with Aurix PPU** (lead: IFAG). The requirements collected in the task are the foundation for developing these demonstrators.

We use the following scheme to collect and compile T1.6 work products of the task members:

1. Partners concentrate on their individual work package tasks and contribute a chapter to T1.6 describing the work executed for T1.6.
2. The task leader provides a template for requirement definition. Partners use the template to collect their requirements and compile them into a separate document.
3. Inputs are reworked and consolidated. Further partners discuss cooperation and requirements alignment in regular meetings.
4. The task leader compiles an aggregation of the developed requirements into this document and documents the approach and achievements.

The following chapter (Introduction & Scope) describes the scope of the document and gives both an introduction and an overview. The main chapter (Requirements and specifications), in which all partners describe their contributions in detail, follows it. Finally, a conclusions chapter sets the work in context to related AI4CSM tasks and summarizes the impact and contributions to the work packages and supply chains.

2 Non publishable information

All the information below is non-publishable.

3 Introduction & Scope

3.1 Purpose and target group

The main purpose of T1.6 is to achieve a foundation upon which the upcoming WP's can perform their research, development, and testing. It sets clear boundaries in which the work must be completed and which outcomes are desired.

The project has pre-written objectives that are divided into the following structure. There are five project objectives O.1.-O.5. which are linked to three SC6-related WP1 objectives O1.1.-O1.3. Being structured in a matrix, those objectives need to be aligned with the SC6 objectives as well. Therefore, the following three subchapters are dedicated to the respective objectives.

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3.1.1 Overall Project Objectives

To understand the main targets and goals of AI4CSM, the main project objectives will be explained as follows:

| Objective # | Title | Expected Output |
|-------------|--|--|
| O1 | Develop Robust and Reliable Mobile Platforms | <p>Innovative technologies for open platforms to bring AI into safety-critical systems.</p> <p>Integration of hardware for AI processing, in the form of high-performance number crunchers and AI accelerators, and microcontrollers with highest levels of safety.</p> <p>Mechanisms to ensure freedom of interference between AI-based and safety-critical software components.</p> <p>Demonstration of architectural concepts to increase the reliability of AI and deal with random HW faults, design faults, as well as how to safeguard AI algorithms (for example, by developing a “doer-checker” framework for AI, supervision of operating conditions, real-time behaviour, etc.).</p> <p>Enabling autonomous driving (perception, path planning, etc.) and supporting digital cockpit, powertrain/drivetrain functions and intelligent autonomous vehicles in manufacturing.</p> |
| O2 | Develop Scalable and Embedded Intelligence for Edge and Edge/Cloud Operation | <p>Cooperative edge/cloud approaches for environment perception and vehicle intelligence enabling safe, efficient, and green shared mobility.</p> <p>Digital twin supporting design, development, verification, validation, and operation of connected shared mobility.</p> <p>Cloud AI-based city routing based on, for example, digital twins.</p> <p>Secure, scalable, and robust communication architectures and systems between agents and cloud.</p> <p>A layered processing approach for robust, reliable, and secure perception and vehicle intelligence.</p> <p>Testing, verification, and validation approaches for connected, shared mobility solutions.</p> |

| | | |
|-----------|--|--|
| 03 | Design Silicon for Deterministic Low Latency and Build AI-Accelerators for Decision and Learning | <p>Specialised processors for the efficient acceleration of cognitive functions in silicon.</p> <p>Scalable computational framework that can realize intelligence at four levels of the automation chain – sensing, cognition, planning, and decision-making.</p> <p>Federated intelligence across multiple layers of the sense-control chain to enable resilient component-level cognition and to allow sensors to produce directly actionable data by virtue of the low-latency operation of the neuromorphic processor.</p> <p>Optimisation of the autonomous system in terms of efficiency, safety, complexity, and cost through computational load redistribution while relaxing the communication needs between the central computing unit and the cloud.</p> |
| 04 | Solve Complexity by Trustable AI in Functional Integrated Systems | <p>Explainable AI methods over larger number of real-world applications.</p> <p>Methods to predict the decision-making when using learned models.</p> <p>Methods to predict the decision-making of models with adversarial inputs.</p> <p>A method that predicts the classification outcome of a system based on separate inputs; slightly modified inputs leading to misclassifications would allow reacting to hostile attacks in a more informed way.</p> <p>Rigorous AI design approaches for improved safety are guaranteed already at design time.</p> |
| 05 | Design Functional Integrated ECS systems | <p>Innovative technologies for open platforms to bring AI into safety-critical systems.</p> <p>Integration of hardware for AI processing, in the form of high-performance number crunchers and AI accelerators, and microcontrollers with highest levels of safety.</p> <p>Mechanisms to ensure freedom of interference between AI-based and safety-critical software components.</p> <p>Demonstration of architectural concepts to increase the reliability of AI and deal with random HW faults, design faults, as well as how to safeguard AI algorithms (for example, by developing a “doer-checker” framework for AI, supervision of operating conditions, real-time behaviour, etc.).</p> <p>Enabling autonomous driving (perception, path planning, etc.) and support of digital cockpit, powertrain/drivetrain functions and intelligent autonomous vehicles in manufacturing.</p> |

Based upon the objectives mentioned above, the following two chapters are derived for more detailed objectives regarding the WP1 and the SC6.

3.1.2 WP1 Objectives

Based on the horizontal WP1 matrix component, specific WP1-related objectives must be taken care of for deriving Requirements and Specifications for SC6.

T1.6 is supposed to cover the following WP1 Objectives:

| Objective # | Title | Description |
|-------------|---|---|
| O1.1. | Requirements and Specifications of Components | Requirements and specifications of semiconductor components, including sensors, computing and connectivity elements, will be defined, directly contributing to the overall project objectives O1 , O2 and O3 . |
| O1.2. | Requirements and Specifications of Subsystems | Expected properties of subsystems (decision, perception, actuation, communication, acceleration) will be defined, including interfaces of individual subsystems. Requirements on subsystems safety and security will be addressed as well as requirements on trustworthy cognitive decision-making and non-causal reasoning systems, directly contributing to the overall project objectives O1 , O2 and O4 . |
| O1.3. | Requirements and Specifications on Vehicle Level | Requirements and specifications on vehicle level will be defined, covering vehicle safety and security, its energy efficiency and demands laid on driving performance, driver support and automated driving functions, directly contributing to the overall project objectives O4 and O5 . |
| O1.4. | Requirements and Specifications for Vehicle Operation in Mission Environment | Requirements and specifications on vehicle operation in natural environment, including interaction with other entities, will be defined. This also includes specifications of V2X cognitive communications and AI based methods for interaction with other vehicles and road users. Specification of interfaces to cloud services (e.g., car sharing platforms, vehicle cooperation based on swarm intelligence, ...) shall be evaluated, directly contributing to the overall project objectives O5 and O6 . |

3.1.3 SC6 Objectives

In the end, the overall and WP1-related objectives will be a general foundation for the newly developed demonstrators in SC6. To understand what needs to be achieved from the SC6-perspective, the objectives are presented on a system and subsystem level.

SC6 addresses the following **Objectives** on **system level**:

- Develop a platform framework to address scalability, functional integration, virtualization, optimisation and software-defined functions by sharing computing resources and connectivity through the fusion of information. Enable load specific and optimised sharing of computing resources composed of a mixture of single- or multi-core CPUs, accelerators, GPUs, FPGAs, NNs, neuromorphic processors, etc.
- The platform framework approach involves distributing intelligence to the perception sensors to facilitate local processing of raw sensor data and implementing a hybrid distributed system architecture that optimizes latency and shares the computing resources at the deep edge where data is pre-processed reducing bandwidth requirements, power consumption, expensive cooling systems etc.
- Define the interfaces and communications protocols and topology for optimally and efficiently shared data and information in a distributed automotive functional domains environment to achieve improved acquisition and perception capabilities for harsh weather and challenging environmental conditions as well as dynamic situations, including unexpected objects.
- Standardisation:
 - addressing the standardisation activities targeting autonomous vehicles and the perception, sensor fusion AI and safety (e.g., ISO/PAS 21448 (SOTIF)
 - addressing the safety of the intended functionality, ISO 26262 aiming at mitigating risk due to system failure, IEEE P2846
 - addressing the formal model for safety consideration in automated vehicle decision-making as AI adds complexity to autonomous vehicle safety analysis, IEEE P2851
 - addressing data format for safety verifications of IP, SoC and mixed-signal ICs, IEEE P1228
 - address autonomous vehicle software safety throughout the vehicle's life cycle, ISO 12813
 - addressing compliance check communication for autonomous systems, ISO 13141
 - addressing localisation augmentation communication for autonomous systems, ISO 22377
 - addressing functional safety for V2V cooperative functions, etc.).

SC6 addresses further **Objectives on subsystem level**:

- Investigate emerging computing paradigms to overcome memory bottlenecks, reduce latency and processing efficiency, and thus facilitate the realisation of the cognitive edge.
- Prototype and validate the developed concepts and designs in silicon and demonstrate their value for automation of safety-critical systems through increased functional integration.
- Develop low-power high-cognition sensors and systems for computationally cheap (cost-efficient) and instantaneous scene interpretation.
- Provide next generation cognitive sensor hardware and embedded software solutions enabling enhanced and instantaneous scene interpretation while minimising its local power consumption and optimising its computational resources/approach.
- Architecture at the component level to address high-performance, energy-efficient AI computing
- Integrate power-efficient AI-enabler components for deep learning neural networks

3.2 Target Group

The Task addresses the requirements and specifications of environment perception and sensor fusion systems and platforms for next-generation electric, connected, autonomous and shared vehicles to address critical operating sensor characteristics used for autonomous vehicles. Therefore, Task 1.6 enables the future mobility developments following the electrification, standardisation, automatization and digitalisation implementation strategy by providing new AI-enabled electronic components and systems for ECAS vehicles for advanced perception, efficient propulsion and batteries, advanced connectivity, further integration and platform concepts and intelligent components based on trustworthy AI. In terms of the AI4CSM consortium, the direct target group consists of the stakeholders who are located in the Supply Chains 2, 3, 4, 5 and 6.

Communication Activities to external stakeholders will be organised, planned and executed within the WP 7 Dissemination, exploitation and standardization. The external target groups will be defined within WP 7. In this project period, the goals, approaches and results of task 1.6 for various target groups will be communicated by establishing contact with key third parties for exploitation.

Potential external target groups consist of:

- Scientific and academic communities who can use the demonstrator and its AL-accelerator with a novel neuromorphic architecture for new exploration and developments.
- Industrial and commercial users, who can use and benefit from significant hardware and software improvements coming from this demonstrator for an automotive application, but also can be extended in various ways beyond this use case.
- General public for general awareness of the latest developments in the neuromorphic field and automotive applications.
- Transportation service providers in public and private sectors, where there is an increased demand for last mile delivery of goods and at the same time reduce environmental impact, including innovative transportation infrastructure and new commercial delivery models based on fleet/platooning of electric vehicles in urban/suburban environment.
- SW engineers of autonomous car production company.
- End-users who can use the developed system for driving assistance.
- ADAS developers who can integrate the system into existing vehicles.
- General public (via dissemination activities for general awareness of automotive technologies).

3.3 Contributions of partners

Leader NXP, Contributing partners: BUT, EDI, IFAG, IFAT, IFI, IFIN, IMA, IMEC, INNAT, NXPDE, NXTECH, PAXSTER, SINTEF, TGLV, TUDELFT

TABLE 1: PARTNER CONTRIBUTIONS

| Chapter | Partner | Contribution |
|---------|---------|-------------------------------|
| All | NXP | Authoring of deliverable T1.6 |

| Chapter | Partner | Contribution |
|---------|---------|--|
| 4 | NXPN | NXPN defines the requirements and specifications of single radar sensor for corner radar use cases, the multi-radar architectures, and the synchronisation methodology for distributed radar. NXPN will also specify high level requirements and building-block architecture of an AI-based prototype reference solution for environment perception and path-planning, which utilises a diverse suite of control and processing processors communicating through a distributed systems communication framework. The activities will describe the state-of-the-art methods that are potentially applicable to this platform to enable realistic AI design, taking properties of this end-node already into account whilst training in the cloud. NXPN as task leader, will coordinate the activities with the partners involved in SC6 for defining the technical requirements and specifications for the different types of perception sensors, and the AI-based HW/SW platforms developed and used in the projects. |
| 4 | BUT | BUT contributes to specification of parallel computing embedded systems suitable for segmentation and extraction of data for multispectral mapping sensors (LiDARs, RGB cameras, thermal imagers, hyperspectral cameras, etc.). |
| 4 | EDI | EDI defines the requirements and specifications for AI based near field, high resolution 360-degree perception system, with special focus on envisioned custom HW and AI based perception algorithms and the demonstrator. |
| 4 | IFAG | IFAG will collect requirements on affordable 360-degrees 3D vehicle-proximity perception/vision systems. Based on those needs, architectural concepts for the utilisation of next generation AURIX microcontroller, including PPU and Infineon's innovative ToF-based 3D sensors subsystems, will be specified. Special focus will be put on the definition of AI functionalities. Related algorithms as well as improvements of the methodology to enable highly effective PPU-application-code generation. An application board architecture and functionality will be specified to become the basis for EDI's board development. The new 3D platform will be used in SC6 and will enable object classification, Intelligent calibration of the image sensor even outside of the factory. As the performance of the sensor system will strongly depend on solutions for the data communication challenges (addressed in SC5) – data network requirements and specifications will also be compiled. |
| 4 | IFAT | IFAT collects and defines requirements for the 3D imaging sensor with focus on the architecture and interfacing between sensor and AI hardware accelerator. IFAT is working on specifying the use cases in detail, such as intelligent calibration during operation (instead of in the factory), mitigation of multi-path reflection effects or sensor authentication. |

| Chapter | Partner | Contribution |
|---------|---------|--|
| 4 | IFI | IFI addresses the definition of the power supply structure for a functional safety PMIC (Power Management IC) suitable to be used in low-cost hybrid 360 ° camera applications. The requirements will be detailed considering the needs for such safety critical application. The targets in terms of acceptable noise levels for the sensors will be discussed since these are known to be a challenging aspect for PMIC development while guaranteeing sensor accuracy. |
| 4 | IFIN | IFIN will support IFAG in the specifications and requirement collection. IFIN will support the definition of perception algorithms and of the related development toolchain (model-based code generation). |
| 4 | IMA | IMA collects stakeholders' requirements on an object and gesture detection in the vehicle's proximity based on the ToF ultrasonic sensing solution. IMA will identify requirements for gesture technology and in cooperation with BUT will specify proper AI decision algorithms. |
| 4 | IMEC | IMEC identifies the computation specifications and requirements for sensor data processing based on a neuromorphic accelerator architecture to achieve high energy efficiency and low latency cognitive inference. |
| 4 | INNAT | INNAT analyses the OEM-defined use-case and accordingly develops a set of requirements and specifications for its neuromorphic accelerator architecture. |
| 4 | NXPDE | NXPDE works on the requirements definition and specifications of coherency for distributed-radar and for antennas in distributed-radar. Further activities address the requirement definition and specification of ISP architecture and AI model framework, including camera-sensor parameters and data sets. |
| 4 | NXTECH | NXTECH defined the requirements and specifications of the electronics and components for perception sensors and sensor fusion techniques to be integrated into small-size ECAS vehicles. The work will identify the design trade-off for the integration of the electronics and components for perception module. |
| 4 | PAXSTER | PAXSTER identifies the technical requirements and specifications for the perception sensors, sensor fusion techniques and the HW/SW platform to be integrated into small-size ECAS vehicles. The work focuses on the definition of the requirements and specifications of local demonstrator for a platooning (2-3 PAXSTER vehicles) use case for delivery of goods into a controlled urban/sub-urban environment. |
| 4 | SINTEF | SINTEF is working on defining and developing the technical requirements and specifications for evaluating and implementing compact, energy efficient and cost-effective perception sensors , sensor fusion techniques and AI-based platforms for delivery of goods integrated into small-size electric, connected autonomous and shared vehicles. The work includes defining the standardisation activities for reliable, safe of autonomous driving perception and sensor fusion functions. |

| Chapter | Partner | Contribution |
|---------|---------|---|
| 4 | TGLV | TGLV defines the requirements and specifications for AI based near field, high resolution 360-degree perception system graphic user interface, with special focus on object visualisation and easy/intuitive perception by a human. |
| 4 | TUDELFT | TUDELFT will define the scope of the architecture space for its exploration in the context of the neuromorphic accelerator development of INNAT. |

3.4 Relation to other activities in the project

As being part of Work Package 1, which defines the system requirements as well as the use cases and validation methodologies, the following inputs are taken into account in the elaboration of Task 1.6:

TABLE 2: INPUT RELATIONS

| Workplan element | Input |
|--|--|
| Task 1.2 [SC2]: Requirements and specifications for the AI based EV demonstrator | BUT will define requirements and specification for the implementation of the cognitive diagnostic system for real time fault detection of the propulsion system on the AURIX platform with PPU and subsequent in-vehicle integration. IFAG will collect SC2 application requirements on microcontroller, 28 GHz communication and 3D object recognition semiconductors. Related specifications for the product chips and the application boards will be deduced. For the code generation for the execution of AI algorithms, the needs for methodology and tooling will be discussed with the SC2 partners. As BUT and IFAG are both parts of the T1.6 and T1.2 an interconnection of the findings in the requirement definition for AI-enabled perception and sensors fusion systems, and platforms is given. |
| Task 1.3 [SC3]: Requirements and specifications for L3 driving and multimodal CSM | IFAG will contribute to driving system definition by deriving controller and communication ECS specification. IFAG will collect SC3 application requirements on microcontroller, 28 GHz communication and 3D object recognition semiconductors. IFI will contribute to the analysis of the power supply backbone to be used in the novel cognitive decision platform for driver's state monitoring. As IFAG and IFI are both parts of the T1.6 and T1.3 an interconnection of the findings in the requirement definition for AI-enabled perception and sensors fusion systems and platforms is given. |
| Task 1.4 [SC4]: Requirements and specifications for the robust propulsion and energy storage system | BUT will contribute to specifications of cognitive control and diagnostics systems for powertrains. IFAG will contribute to powertrain control system definition by providing controller AI ECS specifications. IFAT will define requirements and set up the specification for an advanced mathematical mission profile model. It should be versatile to be used for AI methods at product verification as well as for reliability assessments. IFI will define the power supply backbone for the low-voltage section of the powertrain application in target by SC4. As BUT, IFAG, IFAT and IFI are both part of the T1.6 and T1.4 an interconnection of the findings in the requirement definition for AI-enabled perception and sensors fusion systems and platforms is given. |

| Workplan element | Input |
|---|---|
| Task 1.5 [SC5]: Requirements and specifications for Connectivity and Communications | NXPEN will contribute to the identification and specification of the required cross protocol, in-car communication architecture for SC5 with the other partners, with specific emphasis on its low latency and functional safety requirements. IFAG will specify a complete 5G 28GHz RF Connectivity Frontend targeting deterministic latency and high data rate (1Gbps) V2X communication being able to support ASIL C/D safety levels. NXPDE will contribute to the identification, definition, and collection of the security use cases for the envisioned in-car communication architecture in SC5. As NXPEN, IFAG and NXPDE are both parts of the T1.6 and T1.4 an interconnection of the findings in the requirement definition for AI-enabled perception and sensors fusion systems, and platforms is given. |

The outputs of the Task 1.6 Requirements and specifications for Connectivity and Communications will be used for consecutive WPs, SCs and Tasks:

TABLE 3: T1.6 OUTPUT RELATIONS

| Workplan element | Output |
|---|---|
| Task 2.2 [SC2]: System level design for the AI based EV demonstrator | BUT will perform an architecture analysis based on MBAG inputs and carry out necessary adaptations to in-vehicle integration of the powertrain diagnostic system running inside the novel AURIX platform with PPU. |
| Task 2.3 [SC3]: System level design for L3 driving and multimodal CSM | IFAG will perform system architecture development by addressing control as well as communication aspects. IFI will exploit the system level requirements to define the proper architecture for the power management integrated device, including its safety concept design. |
| Task 2.4 [SC4]: System level design for the robust propulsion and energy storage system | BUT will simulate and analyse computational complexity of cognitive control and diagnostic system. Simulation of cognitive diagnostics using real and virtual sensors based on AI will be performed. IFAG will perform modelling and simulation of the PPU (Parallel processing unit) as part of the 3rd Generation AURIX processor platform for generic AI acceleration to evaluate the performance of the computing platform for AI applications in powertrain systems. IFI will make use of high-level simulations and related model creation to depict the proper architecture and safety concept for the PMIC (power management IC). IFAT will focus on the High-Speed Sensor Interface and the Mission Profile Model. IFAT will perform system level simulations applying this new high-speed sensor interface and provides comparison figures to existing sensor-interfaces. |
| Task 2.5 [SC5]: System level design for Connectivity and Communications | NXPEN will perform modelling and feasibility studies of the cross protocol, in-car communication architecture as specified in WP1, applying network traffic engineering technologies and investigating the specified low latency, safety and Ethernet security requirements. NXPDE will in detail study and design the security means of the cross protocol, in-car communication architecture specified in WP1, based on the outcome of the security use cases as identified and defined in WP1. Special attention will be paid to the security in the CAN (sub)systems. |

| Workplan element | Output |
|--|--|
| Task 2.6 [SC6]: System level design for AI-enabled perception and sensors fusion systems | The task provides the system and subsystem level designs based on the technical requirements and specifications developed in WP1. The designs descriptions include different types of perception sensors, sensor fusion techniques and HW/SW AI-based platforms. The work will describe the AI software and hardware components (including the microcontrollers with AI based functions, perception sensors devices to run analysis to provide results in real-time, etc.) the building blocks, and the properties, functionalities and interactions between the functional subsystems. The designs will include the definitions of subsystem interfaces for seamless integrations into the vehicle platforms. |

4 Description of the technical work

4.1 SCD 6.1 - Perception and vehicle intelligence platform

Demonstrator SCD6.1, “Environment perception and vehicle intelligence platform”, consists of 3 demonstrators sharing similar goals and (partially) common technology. 2 sub-demonstrators relate to improving the image quality of Camera- and Radar-input-data for the environment perception and the 3rd sub- demonstrator aims for the best trade-off of quality of the environment perception measured through accuracy/precision, in combination with a second platform-related objective, e.g. latency or memory-usage etc. This multi-objective optimisation is achieved via a training-process that takes the properties of the inferencing platform into account. The sub-demonstrators further use common technologies of the platform (the “BlueBox”).

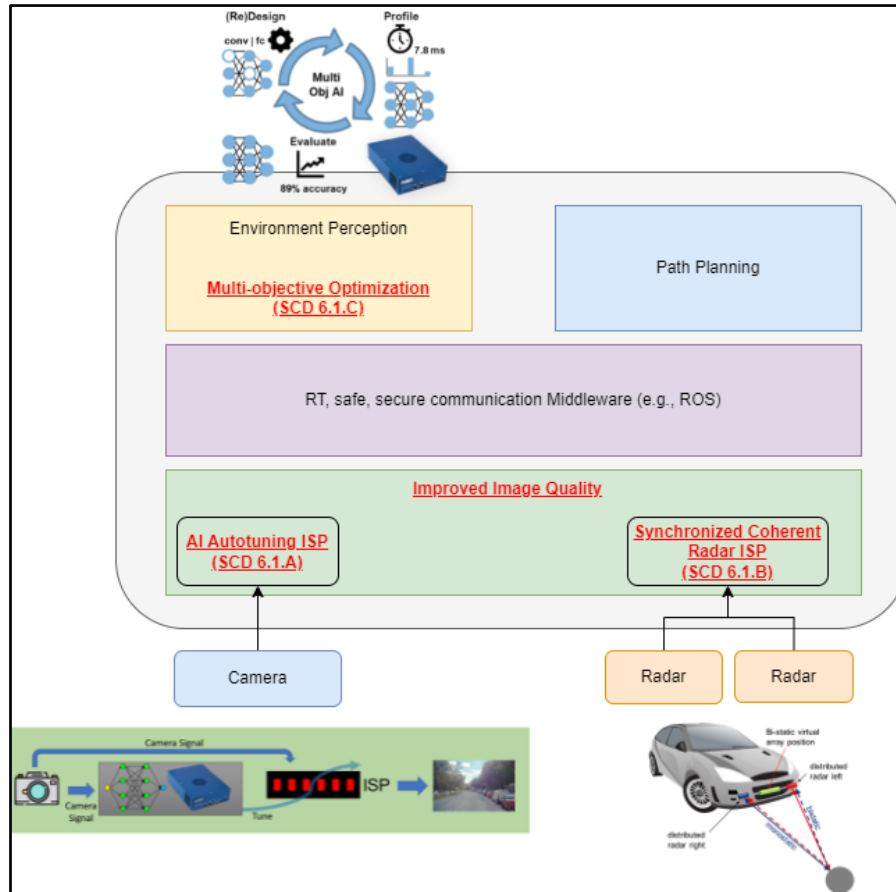


FIGURE 1: SCD 6.1 OVERVIEW

The demonstrator SCD 6.1 by NXP is split into the three subsections Camera Image Improvement, Radar Image Improvement and Neural Networking. Significant improvements in these subsections as well as the merging of them, will be the goal of this demonstrator. The following chapters will be split into the respective subsections as follows.

4.1.1 Demonstrator description

SCD 6.1.A:

Part A will be NXP's plan to implement an AI based solution for tuning Image Signal Processor (ISP) on a car. This solution will improve the resulting image quality compared to conventional methods and decrease labour costs and efforts of finding optimal parameters for creating reference scenarios. Generally, an ISP is tested with standardised image patterns as inputs. These patterns are provided by Standards such as ISO 12233, 16505, etc. In conventional methods, ISP would be tuned for a small set of image scenarios by an expert. Then a state machine will select optimal tuning parameters based on an estimated scenario of the image. This process is costly and not scalable since a number of scenarios could not be expanded. The whole tuning process should be redone and adapted for each camera sensor separately.

In our project, various distortions are added to patterns similar to ISO 12233, 16505, etc standards for simulating camera behaviour and creating artificial inputs for ISP. The positive aspects of the method are:

- The dataset will cover larger range of distortions and combination of them compared to focusing on single camera in laboratory condition for generating data.
- The size of dataset is linearly scalable. Having a large dataset was not feasible with conventional method (using real camera output).

In offline phase, a reinforcement learning algorithm will find the optimal ISP parameters for each distorted image patterns in a dataset. Having optimal parameters and distorted image input, ISP can enhance image quality and fidelity, which is crucial for both human and computer perception. The distorted image patterns and corresponding optimal parameters are collected in a large database.

In the next step, NXP-DeepTuner will be trained to predict the tuning database behaviour. This model is a convolutional neural network (CNN). NXP-DeepTuner will be capable of automatically predicting the ISP parameters for enhancing ISP output image in real-time. The trained model will be tested on computers with various real images. BlueBox is selected as an automotive platform to test the proposed algorithm performance in real time with video stream data.

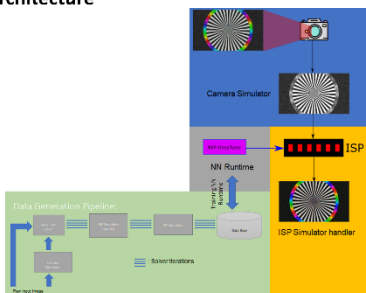
| | |
|--|---|
| <p>1. UC Presentation: (all preliminary, since it can change over time)</p> <p>Demo:</p> <ul style="list-style-type: none"> • Image pre-processing for perception AI models, and high image quality image for driver display (rear and back cameras). <p>Main Added Value:</p> <ul style="list-style-type: none"> • Optimal tuning during runtime • High quality image resulting in various lighting conditions regardless of camera type | <p>3. Main functions developed and mapped to HL Objectives sometimes the function services multiple objectives</p> <ul style="list-style-type: none"> • Find best configurations for ISP offline in PC for a dataset of distorted image patterns. • Trained model will be used in runtime for inference. |
| <p>2. High Level System Architecture</p>  <p>The diagram illustrates the system architecture. It shows a 'Data Generation Pipeline' on the left, which includes 'Real-time image' input, 'Distortions', and 'ISP' blocks. This pipeline feeds into a 'Camera Simulator' and an 'ISP Simulator handler'. The 'Camera Simulator' outputs to an 'NN Runtime' block, which then feeds into an 'ISP' block. The 'ISP Simulator handler' also feeds into the 'ISP' block. The final output is a 'Distorted image'.</p> | <p>4. Key development steps to be undertaken</p> <ol style="list-style-type: none"> 1. Definition of KPIs for image disturbances types (Noise, colorcast, etc) 2. Creation of dataset(s) for mapping camera signals with distortion to optimal ISP parameters 3. Training ML model (DeepTuner) with generated dataset(s) 4. Deploying DeepTuner on bluebox for tuning ISP during runtime 5. Measuring results with Perceptual Loss (VGG Loss) |

FIGURE 2: SCD 6.1.A OVERVIEW

SCD 6.1.B:

Part B will be the demonstration that object detection of an automotive radar system can be improved by substituting one big central front radar sensor with multiple (two) smaller radar sensors. The improved object detection is characterised by a better spatial estimation and a higher probability of detecting objects and therefore leads to an improved radar image quality.

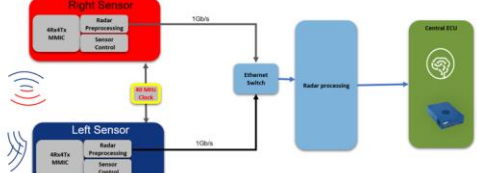
| <p>1. UC Presentation: (all preliminary, since it can change over time) Demo:</p> <ul style="list-style-type: none"> Coherent operation of 2 radar sensors that are distributed over the fascia of a car Fine synchronization of coarsely synchronized radar sensors such that coherent target detection can be carried out <p>Main Added Value:</p> <ul style="list-style-type: none"> Replacement of a large radar sensor by cooperating smaller radar sensors without sacrificing target resolving capabilities Modular radar functionality | <p>3. Main functions developed and mapped to HL Objectives sometimes the function services multiple objectives</p> <table border="1"> <thead> <tr> <th>HL Objective / KPI from FPP</th><th>Functions/Functionality (Bullet)</th></tr> </thead> <tbody> <tr> <td>Improve radar image quality</td><td>Combine data from multiple radar systems</td></tr> <tr> <td></td><td>Synchronize multiple radars</td></tr> <tr> <td></td><td>Improve angular resolution</td></tr> <tr> <td></td><td>Improve target detection probability</td></tr> </tbody> </table> | HL Objective / KPI from FPP | Functions/Functionality (Bullet) | Improve radar image quality | Combine data from multiple radar systems | | Synchronize multiple radars | | Improve angular resolution | | Improve target detection probability |
|--|---|-----------------------------|----------------------------------|-----------------------------|--|--|-----------------------------|--|----------------------------|--|--------------------------------------|
| HL Objective / KPI from FPP | Functions/Functionality (Bullet) | | | | | | | | | | |
| Improve radar image quality | Combine data from multiple radar systems | | | | | | | | | | |
| | Synchronize multiple radars | | | | | | | | | | |
| | Improve angular resolution | | | | | | | | | | |
| | Improve target detection probability | | | | | | | | | | |
| <p>2. High Level System Architecture: HL Design w hw/sw Building Blocks Demonstrator: two coarsely synchronized radar sensors that by means of digital signal processing are synchronized tightly and combining data to carry out coherent target detections</p>  | <p>4. Key development steps to be undertaken; the really novel steps (differentiators) should be highlighted</p> <ul style="list-style-type: none"> Timing offset estimation and correction Carrier phase offset estimation and correction Estimation and compensation of correlated phase noise Coherent target (Direction-of-Arrival) estimation | | | | | | | | | | |

FIGURE 3: SCD 6.1.B OVERVIEW

SCD 6.1.C:

Part C will demonstrate a vision-based AI application that has been trained in the cloud whilst taking the properties of the inference edge-node, the reference automotive environment perception platform, into account. The platform consists of a diverse suite of control and processing processors, including AI accelerators. It is expected that current typical bottlenecks and problems that are encountered in the deployment of state-of-the-art neural networks on inference edge-nodes (such as latency, memory, supported operations, bandwidth) are mitigated in doing so, leading to more performant and easier deployed application on lower cost platforms.

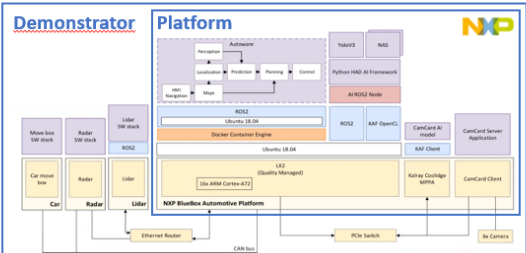
| <p>1. UC Presentation: (all preliminary, since it can change over time) Demo:</p> <ul style="list-style-type: none"> Multi-objective optimization applied to an ADAS environment perception use-case Open-source-enabled environment perception platform Communication middleware across compute nodes <p>Main Added Value:</p> <ul style="list-style-type: none"> Improved model performance tailored to inference node qualities Ensured compatibility with edge nodes at design-time Eco-system enablement | <p>3. Main functions developed and mapped to HL Objectives sometimes the function services multiple objectives</p> <table border="1"> <thead> <tr> <th>HL Objective / KPI from FPP</th><th>Functions/Functionality (Bullet)</th></tr> </thead> <tbody> <tr> <td>O1: AI optimization strategy designed to improve model performance on edge platforms / KPI: Improved accuracy [%] and inference latency [s]</td><td>AI model performance boosts (higher accuracy and lower latency)</td></tr> <tr> <td>O4: Automated model design for improved performance, and compatibility with edge nodes at design-time / KPI: Compatibility of AI models with target inference nodes</td><td>Deployability of optimized models on target edge nodes</td></tr> <tr> <td>O3: Scalable computational eco-system that can realize intelligence at four levels of the automation chain / KPI:</td><td>Eco-system enablement via open-source-enabled platform (e.g., via Autoware/Apollo)</td></tr> </tbody> </table> | HL Objective / KPI from FPP | Functions/Functionality (Bullet) | O1: AI optimization strategy designed to improve model performance on edge platforms / KPI: Improved accuracy [%] and inference latency [s] | AI model performance boosts (higher accuracy and lower latency) | O4: Automated model design for improved performance, and compatibility with edge nodes at design-time / KPI: Compatibility of AI models with target inference nodes | Deployability of optimized models on target edge nodes | O3: Scalable computational eco-system that can realize intelligence at four levels of the automation chain / KPI: | Eco-system enablement via open-source-enabled platform (e.g., via Autoware/Apollo) |
|---|--|-----------------------------|----------------------------------|---|---|---|--|---|--|
| HL Objective / KPI from FPP | Functions/Functionality (Bullet) | | | | | | | | |
| O1: AI optimization strategy designed to improve model performance on edge platforms / KPI: Improved accuracy [%] and inference latency [s] | AI model performance boosts (higher accuracy and lower latency) | | | | | | | | |
| O4: Automated model design for improved performance, and compatibility with edge nodes at design-time / KPI: Compatibility of AI models with target inference nodes | Deployability of optimized models on target edge nodes | | | | | | | | |
| O3: Scalable computational eco-system that can realize intelligence at four levels of the automation chain / KPI: | Eco-system enablement via open-source-enabled platform (e.g., via Autoware/Apollo) | | | | | | | | |
| <p>2. High Level System Architecture: HL Design w hw/sw Building Blocks Demonstrator: HAD platform integration on NXP vehicle</p>  | <p>4. Key development steps to be undertaken; the really novel steps (differentiators) should be highlighted</p> <ul style="list-style-type: none"> AI designing AI: AI optimization methodologies targeted towards NXP Inference nodes Open-source enablement with AI-platform Enabling middleware across compute nodes Platform design and low-level enablement | | | | | | | | |

FIGURE 4: SCD 6.1.C OVERVIEW

4.1.2 Objectives

SCD 6.1.A:

- Creating a solver pipeline (Reinforcement learning method) for finding optimal ISP parameters for different camera scenes (Optimisation pipeline)
- Creating a camera simulator for mimicking a real, imperfect sensor behaviour
- Create a database of disturbing images and the optimal ISP parameters to correct them which could be used in other projects
- Train NXP-DeepTuner model with the dataset. The trained model can be run on BlueBox for inferencing the optimal ISP parameters for real video stream.

SCD 6.1.B:

- Demonstrate feasibility of replacing one big radar sensor with multiple (two) smaller radar sensors
- Synchronise multiple radars in time and frequency (correction of the carrier phase offset)
- Improve object detection with higher spatial resolving capability, especially in angular domain
- Improve object detection by lowering probability of misdetection of a target

SCD 6.1.C:

- Achieve accurate and efficient execution of image recognition for ADAS on a perception and vehicle intelligence platform.
- Improve performance of state-of-the-art models on edge platforms by taking the inference node properties into account during the training process.
- Ensure compatibility of trained models with edge nodes by taking unsupported operations into account during the training process.
- Enable a flexible and scalable eco-system via an open-source enabled environment perception platform.

4.1.3 Alignment to the project and SC6 objectives

SCD 6.1.A:

The following overall objectives are addressed:

- **O1:** Enabling autonomous driving by directly influencing the perception qualities and therefore enhancing navigation.
- **O2:** Improving the ISP will enhance and secure the perception of intelligent vehicles.
- **O3:** The improved quality of perception supports computational frameworks in regard to perception. Additional computation caused by low quality images can be reduced.
- **O4:** Solve Complexity by Trustable AI in Functional Integrated Systems: It is vital for computer vision system to receive image with high fidelity for distinguishing objects, pedestrians, other vehicles, etc.
- **O5:** Enabling autonomous driving by providing improved perception. NXP-DeepTuner will improve input image quality of ADAS algorithms by tuning ISP during runtime and, as results, increases their safety.

The following WP1 objectives are addressed by the demonstrator:

- **O1.2:** Tuning the ISP is an improvement of a subsystem of a perception sensor, in this case, the camera. It addresses requirements on trustworthy cognitive decision-making but improves the perception quality.
- **O1.3:** On vehicle level, the safety and security are benefitting from better quality perception. It will support automated driving by enhancing the perception of the environment.

The following SC6 objectives are addressed by the demonstrator:

- The platform framework approach involves distributing intelligence to the perception sensors: Creating an AI based tuning tool for ISP results, obtaining a higher image perception quality from the camera. This high-quality image will be used as an input for higher level AI algorithms that perceive the scene scenario and decide the driving strategy.

SCD 6.1.B:

The following overall objectives are addressed:

- **O1:** Enabling autonomous driving (perception, path planning, etc.), and support of digital cockpit, powertrain/drivetrain functions and intelligent autonomous vehicles in manufacturing.
- **O3:** Optimised of the autonomous system in terms of efficiency, safety, complexity, and cost through computational load redistribution while relaxing the communication needs between the central computing unit and the cloud.

The following WP1 objectives are addressed by the demonstrator:

- **O1.1:** The sensors and computing elements comprising the demonstrator are specified.
- **O1.2:** Platform subsystems are specified, including expected properties and interfaces of individual subsystems.

The following SC6 objectives are addressed by the demonstrator:

- Develop a platform framework to address scalability, functional integration, optimisation, software-defined functions by sharing computing resources and connectivity through the fusion of information. Enable load specific and optimised sharing of computing resources composed of a mixture of single- or multi-core CPUs and accelerators.

Define the interfaces for optimally and efficiently shared data and information in a distributed automotive functional domains environment to achieve improved perception capabilities for harsh weather and challenging environmental conditions.

SCD 6.1.C:

The following overall project objectives are addressed:

- **O1:** Integration of an edge platform comprised of a mixture of processing elements, including an AI accelerator for reliable and efficient computing at the edge.
- **O1:** Implementation of an AI optimisation strategy designed to improve model performance on edge platforms (higher accuracy and lower latency).
- **O4:** Automated model design for improved performance and compatibility with edge nodes at design-time.
- **O3:** Scalable computational eco-system that can realize intelligence at four levels of the automation chain.

The following WP1 objectives are addressed by the demonstrator:

- **O.1.1:** The sensors and computing elements comprising the demonstrator are specified.
- **O.1.2:** Platform subsystems are specified, including expected properties and interfaces of individual subsystems.

The following SC6 objectives are addressed by the demonstrator:

- Develop a platform that addresses high performance and scalability via integrating a mixture of processing elements, including AI accelerators, with a highly flexible open-source enabled software eco-system.
- Investigate novel paradigms to improve AI processing efficiency by taking into account the properties of the edge inferencing node.

4.1.4 Partners and their role

SCD 6.1.A:

NXPDE is responsible for the training of the utilised dataset and implementation of the trained DeepTuner.

SCD 6.1.B:

NXPDE is responsible for the coherent distributed radar demonstrator development, which includes both HW modifications of existing radar sensors and SW development (algorithms and control code).

SCD 6.1.C:

NXPDE prototypes the environment perception platform and provides a demonstration of the benefits of their NN training process for vision on the platform.

4.1.5 Demonstrator architecture

SCD 6.1.A:

Part A of the demonstrator consists of the two sections. One section is for data training and one for implementing the trained DeepTuner. How the DeepTuner is implemented is described as follows:

1. A digital camera for capturing image and convert it to digital signal.
2. BlueBox which runs the NXP-DeepTuner model for inferencing optimal ISP parameters.
3. ISP which converts camera signal to perceptually correct image.

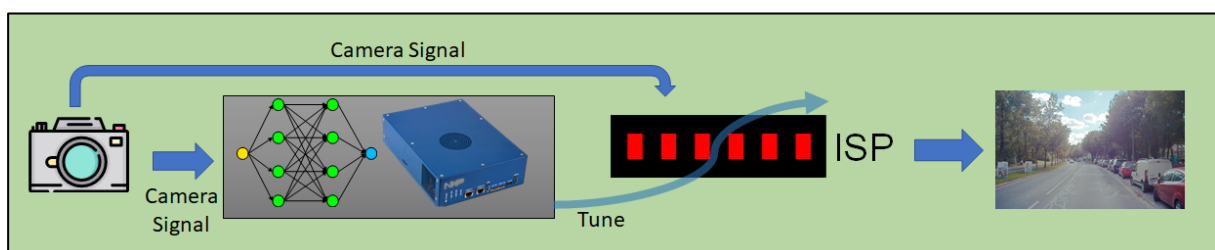


FIGURE 5: SCD 6.1.A ISP TUNING ARCHITECTURE

The DeepTuner has to be trained before it can be used for inferencing optimal ISP parameters. For the training, a dataset with direct mapping between camera signal and optimal ISP parameters is required. Creating such a dataset requires huge expert efforts if it is done manually and will not be scalable to

enough scenarios. For automatising dataset generation, we have a software architecture, as shown in Figure 6. It consists of the following elements:

1. Camera simulator: It creates a realistic camera signal (Bayer pattern) from an image of scene by adding specific distortion (Noise, colour casting, etc.) and adds it to database
2. ISP Simulator Handler: A C-Simulator for mimicking ISP hardware is wrapped inside a rust application. This software block instantiates multiple ISPs in parallel and handles data conversion between data generation pipeline and C-Simulator instances
3. Data generation (Optimisation) Pipeline: Reinforcement learning process for finding best ISP parameter for each Camera signal we have in database and creates a dataset for mapping image signals to optimal ISP parameters
4. DeepTuner: ML model which will be trained with points we have in dataset. The trained model will be used in demonstrator for inferencing optimal ISP during runtime.

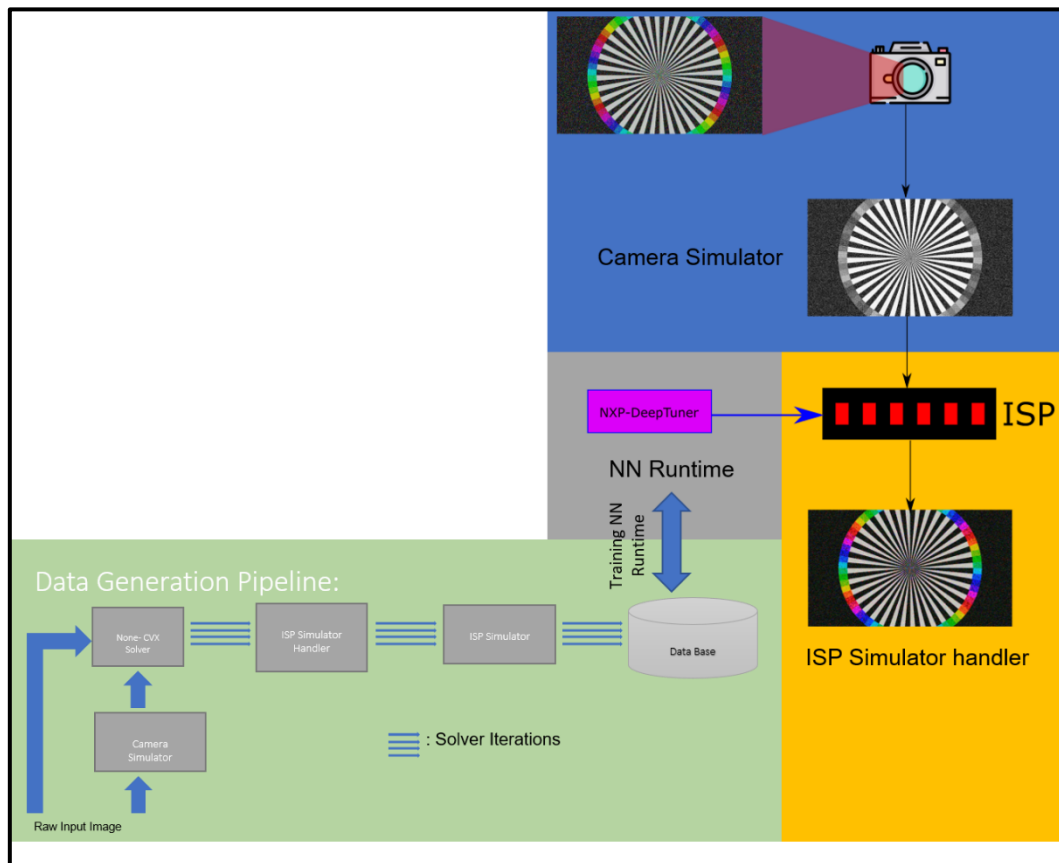


FIGURE 6: SCD 6.1.A DATASET TRAINING ARCHITECTURE

SCD 6.1.B:

The coherent distributed radar will consist of two radar sensors. To demonstrate the concept of coherent distributed radar, these sensors are fed with a central 40 MHz reference clock to let them operate in a coarsely synchronised way. The data collected by the two sensors is brought via Ethernet interface to a central Radar processing unit, where tight synchronization and combining data is carried out. The combining of data involves improved detection of objects regarding their location (radial distance and azimuth) and radial velocity. As such, the demonstrator is supposed to improve the radar

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image quality as it can be further analysed and processed by in a central ECU, e.g. the blue box. The further analysis and processing of the improved radar image are not within the scope of the demonstrator.

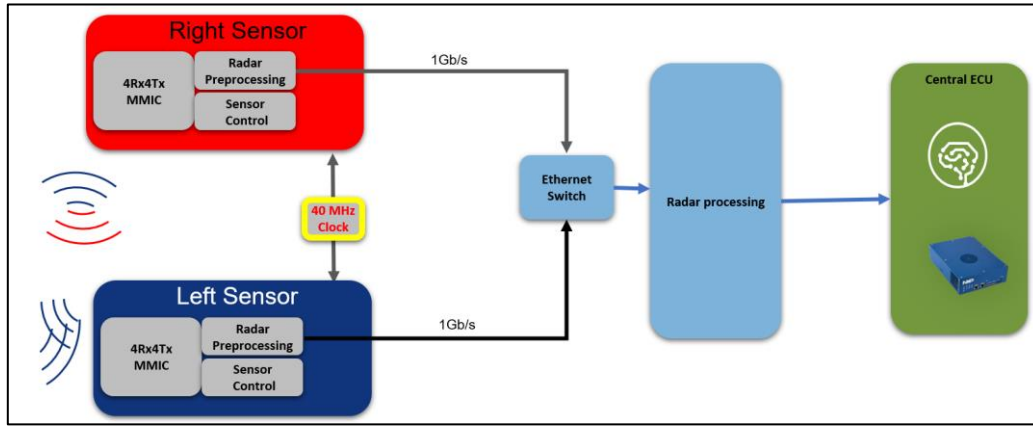


FIGURE 7: SCD 6.1.B COHERENT DISTRIBUTED RADAR DEMONSTRATOR

SCD 6.1.C:

The environment perception platform with its Software Development Kit interfaces to vision and radar sensors and to the Kalray Massively Parallel Processor Array.

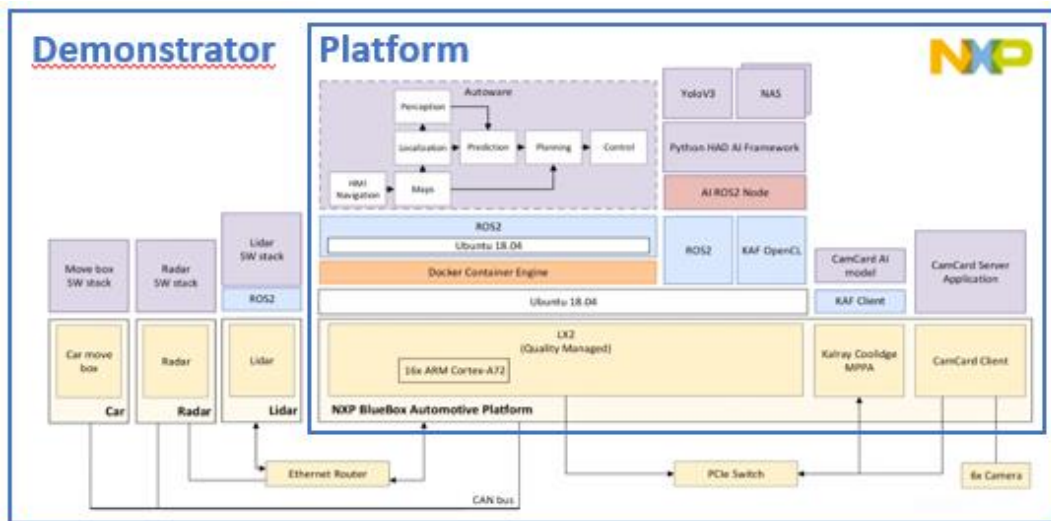


FIGURE 8: SCD 6.1.C HAD PLATFORM INTEGRATION ON NXP VEHICLE

4.1.6 Requirements

TABLE 4: #1 FR SCD 6.1.A

| | #1 Functional Requirements / FR |
|------------------|---|
| ID | AI4CSM_SC6_D1-1 |
| FR Naming | Perceptual similarity |
| Definition of FR | $l_{VGG/i,j} = \frac{1}{W_{i,j}H_{i,j}} \sum_{x=1}^{W_{i,j}} \sum_{y=1}^{H_{i,j}} \left(\phi_{i,j}(I^{HR})_{x,y} - \phi_{i,j}(G_{\theta_G}(I^{LR}))_{x,y} \right)^2$ |

| | |
|--------------------------------------|--|
| | $\phi_{i,j}$: VGG NN I^{HR} : reference image I^{LR} : distorted image $G_{\theta_G}(I^{LR})$: reconstructed image by ISP $W_{i,j}H_{i,j}$: image dimensions |
| Description of FR | For perceptual similarity, VGG loss is selected. It is a content aware method for measuring Perceptual loss of a reference and reconstructed image. In contrast with pixel-wise comparison methods such as PSNR, it attempts to prioritise perceptual similarity of two images instead of pure pixel value comparison. |
| What is measured: | Reconstructed image output of image signal processing (ISP) will be compared with the reference with VGG loss. |
| KPI | VGG loss |
| Method of collection and measurement | A reference image will be converted to Bayer pattern, and disturbances (Noise, colour casting, etc.) will be added to it. Then Bayer pattern will be fed to ISP, and the reconstructed image from ISP will be compared with reference image by computing VGG loss. |
| Target Value | 20% increase in VGG loss after tuning ISP |
| Verification and validation method | Camera signal from specific scene (printed reference image) will be reconstructed with tuned ISP, and VGG loss will be computed by having reference image. |

TABLE 5: #2 FR SCD 6.1.B

| | #2 Functional Requirements / FR |
|--------------------------------------|--|
| ID | AI4CSM_SC6_D1-2 |
| FR Naming | Angular separation |
| Definition of FR | The system shall be able to resolve two equally large objects at the same distance with an angular separation that is larger or equal to 2 degrees |
| Description of FR | Use of 2 distributed and synchronised sensors to resolve targets in angular domain |
| What is measured: | Two objects at same radial distance with small angular separation |
| KPI | [deg] separation |
| Method of collection and measurement | Two corner reflectors will be placed at 20 m distance from the distributed radar sensor. Separation of corner reflectors will be varied such that angular separation changes accordingly. Radar data will be collected and processed. Direction-of-Arrival estimation will be carried out in order to estimate angular position of targets. With too small separation, only one target will be detected. |
| Target Value | 2 degrees |
| Verification and validation method | Experiment to be repeated several times, in $\geq 90\%$ of the cases two targets must be detected in case of 2 degrees separation. |

TABLE 6: #3 FR SCD6.1.C

| | #3 Functional Requirements / FR |
|----|---------------------------------|
| ID | AI4CSM_SC6_D1-3 |

| | |
|--------------------------------------|---|
| FR Naming | Multi-objective Optimisation |
| Definition of FR | The system shall concurrently optimise a CNN for a reference application to improve the accuracy of predictions while reducing inference latency on the target platform |
| Description of FR | The multi-objective optimisation shall automatically design a CNN for a reference application to achieve high accuracy and low latency on the target inferencing platform |
| What is measured: | Model accuracy and inference latency |
| KPI | [%] Accuracy and [s] Latency |
| Method of collection and measurement | The accuracy of the optimised network will be measured on the dataset used to optimise the CNN and benchmarked with comparable SOTA networks. The inference latency of the network will be measured on the target platform. |
| Target Value | An accuracy increase and latency reduction over comparable SOTA networks |
| Verification and validation method | Dataset accuracy and inference latency measured on the target platform. |

TABLE 7: #1 NFR SCD 6.1.A

| | #1 Non-Functional Requirements / NFR |
|--------------------------------------|---|
| ID | AI4CSM_SC6_D1-4 |
| NFR Naming | Inference speed (Tuning speed on Bluebox) |
| Definition of NFR | DeepTuner should run fast on ARM NPU/ Accelerator |
| Description of NFR | Trained NN for tuning ISP(DeepTuner) should be fast. DeepTuner should provide optimal ISP parameter with at most one frame delay. |
| What is measured: | Execution time for inferencing with DeepTuner |
| KPI | FPS |
| Method of collection and measurement | Measuring elapsed time to inference DeepTuner for single image. |
| Target Value | 30fps |
| Verification and validation method | Inferencing trained DeepTuner on ARM platform |

TABLE 8: #2 NFR SCD6.1.B

| | #2 Non-Functional Requirements / NFR |
|--------------------|---|
| ID | AI4CSM_SC6_D1-5 |
| NFR Naming | Distributed radar functionality using two or more smaller radar sensors |
| Definition of NFR | The 2 or more radar sensors should carry out a coherent radar function |
| Description of NFR | Two (or more) radar sensors should be tightly synchronised in order to be able to fuse their radar data and jointly detect and localize targets |
| What is measured: | Radar functionality on base of two or more cooperating radar sensors |
| KPI | Achieved / Not Achieved |

| | |
|--------------------------------------|---|
| Method of collection and measurement | A scene of targets will be configured outdoor together with real-life objects (cars, buildings, persons), and radar will be collected |
| Target Value | A list of detected targets |
| Verification and validation method | The list of detected targets should be reliable (qualitative): not too many undetected targets, not too many ghost targets |

TABLE 9: #3 NFR SCD6.1.C

| | #3 Non-Functional Requirements / NFR |
|--------------------------------------|--|
| ID | AI4CSM_SC6_D1-6 |
| NFR Naming | Optimised CNN compatibility with the target platform |
| Definition of NFR | The optimisation algorithm shall provide means to guarantee that the optimised CNN models are compatible with the target platform and its SDK |
| Description of NFR | The multi-objective optimisation algorithm shall provide means to guarantee that the derived models can be executed on the target inferencing platform for demonstration |
| What is measured: | Compatibility with the target platform and SDK |
| KPI | Achieved / Not achieved [Qualitative] |
| Method of collection and measurement | Experiment(s) will be performed to show the ability of the multi-objective optimisation strategy to guarantee compatibility with the target inference platform |
| Target Value | Algorithm flexibility to disregard/remove unsupported NN operations from the optimisation process, therefore, guaranteeing compatibility with the target platform |
| Verification and validation method | Unsupported NN operations disregarded/removed from the optimisation and optimised model running on the target platform |

Note: Additional requirements will be provided as part of the technical specification in WP2.

4.1.7 Validation, verification, and testing

SCD 6.1.A:

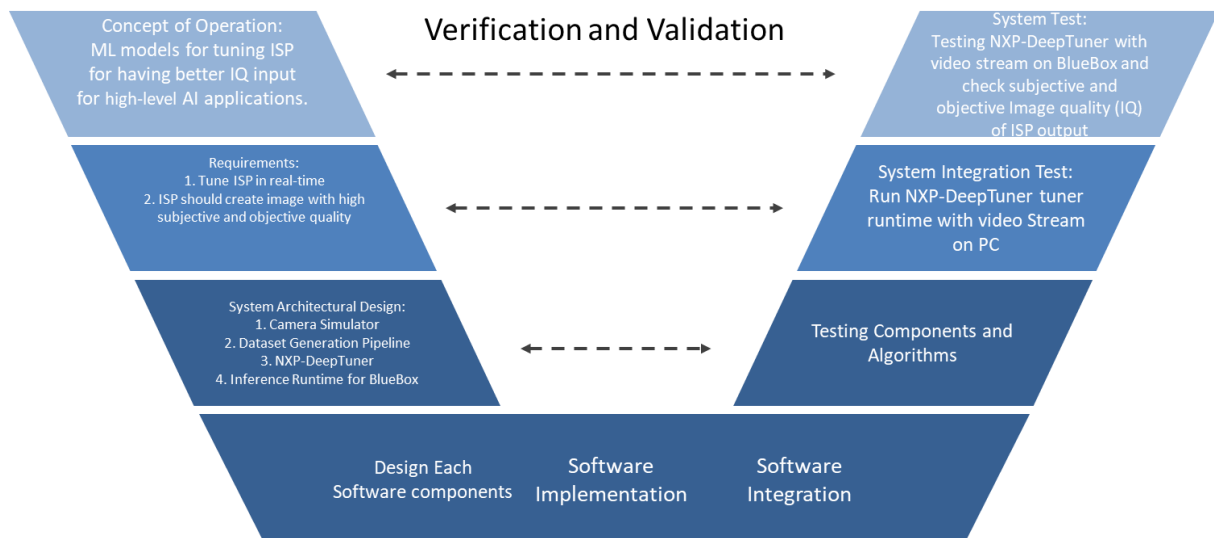


FIGURE 9: SCD 6.1.A VERIFICATION AND VALIDATION CONCEPT

NXPDE will contribute with a novel tuning tool for ISP. A Deep learning (DL) model name NXP-DeepTuner will be utilised for tuning ISP based on the received signal from the camera sensor. NXP-DeepTuner should be trained based on automatic generated dataset. The Data Generation pipeline creates a database with the optimal ISP parameters for a huge set of light and scene conditions. The trained model will be run on Blue Box Platform which infers the optimal ISP parameters based on the image signal received from the camera. The Demonstrator should show that good image quality could be achieved by tuning ISP by DL model in realistic conditions (video stream) on BlueBox platform.

For testing, we are sticking to V-model. Each software component will be tested at lowest level, then trained DeepTuner model will be tested with video stream on PC. At the end, DeepTuner will be run on bluebox as an ARM based system to prove real-time performance as NFR.

SCD 6.1.B:

- **Verification:** The ability to perform radar functionality with the required angular separation will be determined in field tests with dedicated targets (corner reflectors).
- **Validation:** Field tests with two cars in front of the radar system at the same distance will be measured with the radar system, and it will be determined at which distance these cars are detected separately.

SCD 6.1.C:

- **Verification:** The accuracy of the models derived by the algorithm will be evaluated on the dataset used during the optimisation process. Moreover, the inference latency will be measured on the target edge node.
- **Validation:** The prime method for validating the multi-objective optimisation methodology and its added value will be through verifying its ability to improve the derived model's accuracy and inference latency on the target inferencing platform. Additionally, a system integration and qualitative demonstration on the vehicle will be made.

4.2 SCD 6.2 - Neuromorphic sensor fusion

Demonstrator SCD 6.2 – “Neuromorphic sensor fusion” consists of two main parts sharing common AI technologies -- spiking neural network. The demonstrator **SCD 6.2.A** lead by Imec focuses on a hardware-software co-design based on a spiking neural network and embedded processing for automatic detection, tracking and classification of multiple vulnerable road users and vehicles. The demonstrator **SCD 6.2.B** lead by INNAT and TUDelft focuses on the development of a programmable analogue-mixed signal accelerator platform for always-on detection and recognition of time-series patterns in sensor data. The demonstrator utilises spiking neural network algorithms, implemented atop an accelerator fabric for low-latency, ultra-low-power processing.

4.2.1 Demonstrator description

SCD 6.2.A:

This part of the demonstrator is targeting to show substantial benefits in the usage of neuromorphic accelerator based on a spiking neural network architecture in an automotive application. The demonstrator consists of a hardware prototype encapsulating an event-based neuromorphic sensor fusion accelerator for automatic detection, tracking and classification of multiple Vulnerable Road Users (VRU). A novel neural network architecture together with a heterogeneous multi sensor fusion approach will provide a robust, fail-tolerant, power-efficient and low-latency inference for a target application at the deep edge. **Error! Reference source not found.** shows a four quadrant view of this part of the demonstrator.

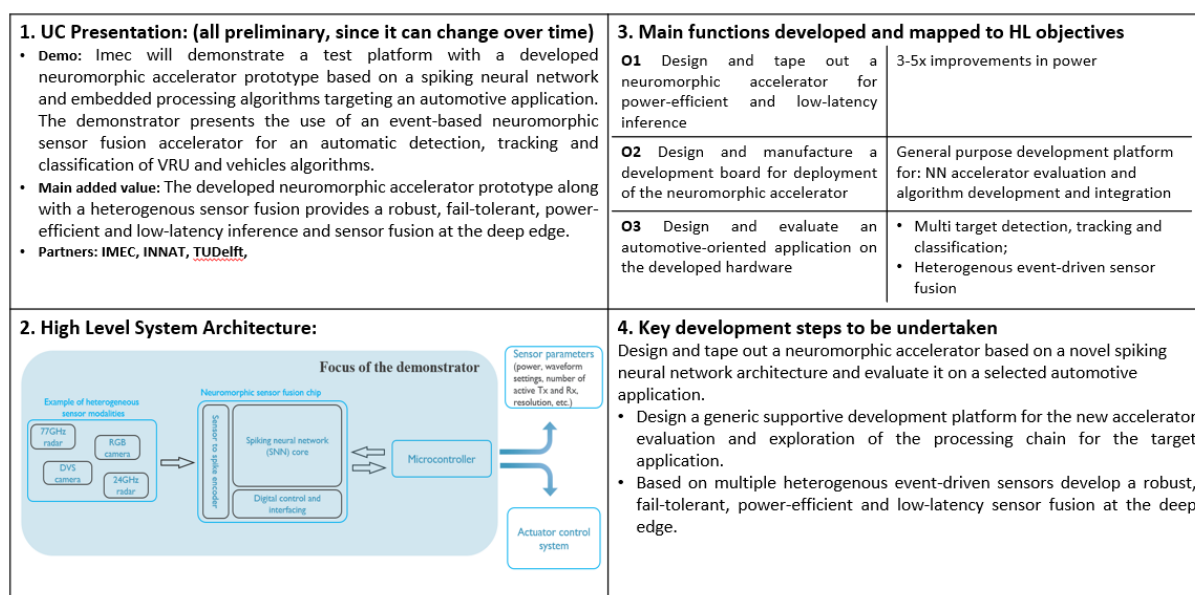


FIGURE 10: SCD 6.2.A OVERVIEW

SCD 6.2.B:

In the second part of Demonstrator 6.2, INNAT and TUDelft focus on realising a demonstration platform that comprises an analogue-mixed signal accelerator for spiking neural networks, running a trained SNN for the detection and recognition of time-series patterns in a live sensor data stream. The demonstrator will comprise the accelerator chip deployed within a pipeline that will include an embedded microcontroller (MCU) or digital signal processor (DSP) for signal conditioning and feature extraction on a data stream. The demonstration will utilise a synthetic sensor data stream injected

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from a PC or emulator into the processor. The demonstrator will show inference in real-time on the data stream, producing labels that correspond to patterns in the stream. Critically, this demonstrator will validate the targeted sub-10mW inference power dissipation required for fast always-on operation in automotive edge use-cases. **Error! Reference source not found.** shows a high-level view of the demonstrator SCD 6.2.B.


| <p>1. UC Presentation: (all preliminary, since it can change over time)</p> <ul style="list-style-type: none"> • Demo: Innat and TUDelft will demonstrate a spiking neural network based engine for processing of time-series signals within a tight latency and power envelope. The demonstrator exhibits the key enabling technologies required on the processing side to realize always-on powertrain/engine monitoring based on pattern recognition. • Main added value: The developed processing solution enables fast detection of failure modes/operational scenarios, in a continuous monitoring paradigm, with negligible power dissipation. This enables the realization of robust, efficient power trains based on embedded intelligence. • Partners: INNAT, TUDelft, | <p>3. Main functions developed and mapped to HL Objectives</p> <table border="1"> <thead> <tr> <th>HL Objective / KPI from FPP</th><th>Functions/Functionality</th></tr> </thead> <tbody> <tr> <td>O2 Develop scalable and embedded intelligence for edge and edge/cloud operation/ KPI: Latency reduction of up to 10x over conventional architecture; Reducing the total power budget below 100mW for edge cognition</td><td> <ul style="list-style-type: none"> • Inference power <10mW • Inference latency <10ms </td></tr> <tr> <td>O3 Design silicon for deterministic low latency and build AI-accelerators for decision and learning/ KPI: Reduce power by a factor 5x compared to current state-of-the-art.</td><td> <ul style="list-style-type: none"> • Inference power <10mW • Inference latency <10ms </td></tr> <tr> <td>O5 - Design functional integrated ECS systems:</td><td> <ul style="list-style-type: none"> • Always-on embedded intelligence within the power train </td></tr> </tbody> </table> | HL Objective / KPI from FPP | Functions/Functionality | O2 Develop scalable and embedded intelligence for edge and edge/cloud operation/ KPI: Latency reduction of up to 10x over conventional architecture; Reducing the total power budget below 100mW for edge cognition | <ul style="list-style-type: none"> • Inference power <10mW • Inference latency <10ms | O3 Design silicon for deterministic low latency and build AI-accelerators for decision and learning/ KPI: Reduce power by a factor 5x compared to current state-of-the-art. | <ul style="list-style-type: none"> • Inference power <10mW • Inference latency <10ms | O5 - Design functional integrated ECS systems: | <ul style="list-style-type: none"> • Always-on embedded intelligence within the power train |
|---|--|-----------------------------|-------------------------|--|--|--|--|---|--|
| HL Objective / KPI from FPP | Functions/Functionality | | | | | | | | |
| O2 Develop scalable and embedded intelligence for edge and edge/cloud operation/ KPI: Latency reduction of up to 10x over conventional architecture; Reducing the total power budget below 100mW for edge cognition | <ul style="list-style-type: none"> • Inference power <10mW • Inference latency <10ms | | | | | | | | |
| O3 Design silicon for deterministic low latency and build AI-accelerators for decision and learning/ KPI: Reduce power by a factor 5x compared to current state-of-the-art. | <ul style="list-style-type: none"> • Inference power <10mW • Inference latency <10ms | | | | | | | | |
| O5 - Design functional integrated ECS systems: | <ul style="list-style-type: none"> • Always-on embedded intelligence within the power train | | | | | | | | |
| <p>2. High Level System Architecture</p>  <pre> graph LR A[Generic Sensor] --> B[MCU/DSP] B --> C[Analog-Mixed Signal Accelerator] C --> D[Pattern label] </pre> | <p>4. Key development steps to be undertaken; the really novel steps (differentiators) should be highlighted</p> <ul style="list-style-type: none"> • Development of spiking neural network based approaches for time-series pattern recognition for the selected application. • Realization of energy-efficient encoder architectures for integration within the accelerator architecture. • Extension of the accelerator fabric with novel intrinsics for low-latency, low-energy inference of the selected application use-case. | | | | | | | | |

FIGURE 11: SCD 6.2.B OVERVIEW

4.2.2 Objectives

SCD 6.2.A:

- Design and develop a neuromorphic accelerator based on a novel spiking neural network architecture to showcase power-efficient and low-latency inference for an automotive application
- Design and manufacture a development board for deployment and demonstration of the neuromorphic accelerator
- Design and evaluate an automotive-oriented application focused on multi target detection, tracking and classification of the developed hardware
- Utilize a multi-sensor approach to demonstrate heterogenous event-driven sensor fusion for robust and fail-tolerant operation

SCD 6.2.B:

- Demonstrate an ultra-low power, low latency analogue-mixed signal accelerator for spiking neural networks
- Develop spiking neural network models for the detection and recognition of time-series patterns in sensor data
- Integrate conventional compute and signal processing hardware with the spiking architecture for always-on operation.

4.2.3 Alignment to the project and SC6 objectives

SCD 6.2.A:

The following overall objectives are addressed:

- **O1:** Hardware and software co-design with a focus on multiple heterogeneous event-driven sensors will support a robust and fail-tolerant sensor fusion at the deep edge.
- **O2:** Developed neuromorphic accelerator, and its platform will be capable of dealing with modifications and extensions in the system & application levels for reliable edge operation.
- **O3:** One of the key objectives is to develop a specialized neuromorphic accelerator based on a spiking neural network for power-efficient and low-latency inference.

The following WP1 objectives are addressed by the demonstrator:

- **O1.1:** Requirements and specifications of the targeted sensors and computational components are specified.

The following SC6 objectives are addressed by the demonstrator:

- Targeted neuromorphic architecture addresses application scalability and functional integration. Together with a conventional computing system provides load specific and optimized sharing of computing resources.
- Proposed system architecture provides flexibility in processing distribution, starting from a local processing of raw data close to a sensor down to partial delegation of processing to specialized accelerators and general-purpose cores. This supports a system's power-efficiency and low-latency at the deep edge.
- A novel neuromorphic architecture based on spiking neural network address at the component level a high-performance and energy-efficient AI computing.

SCD 6.2.B:

This demonstrator addresses the following project objectives:

- **O2:** Develop scalable embedded intelligence for edge and edge/cloud operation. In doing so, the demonstrator contributes to latency and power reduction compared to conventional hardware.
- **O3:** Design silicon for deterministic low latency and build AI accelerators for decision and learning. By deploying analogue-mixed signal silicon specialised for spiking neural network acceleration, this demonstrator contributes to the power reduction targeted in this objective.
- **O5:** Design functional integrated ECS systems. This demonstrator realises always-on embedded intelligence functionalities that facilitate embedded pattern recognition within the powertrain for improved safety and reliability.

The following WP1 objectives are addressed by the demonstrator:

- **O1.1:** Requirements and specifications of the targeted sensors and computational components are specified.

The following SC6 objectives are addressed by this demonstrator:

- The demonstrator presents a novel approach based on spiking neural networks that enables high-performance always-on intelligence embedded within sensor-driven components within the vehicle.

- The architecture enables federated intelligence across the vehicular platform, starting with integrating ultra-low power, always-on processing capabilities at the sensor edge.

4.2.4 Partners and their role

SCD 6.2.A:

Imec is responsible for developing a prototype of a neuromorphic accelerator based on a spiking neural network and embedded processing algorithms targeting an event-based neuromorphic sensor fusion accelerator for automatic detection, tracking and classification of VRU.

SCD 6.2.B:

INNAT is responsible for developing the system architecture of the accelerator platform, as well as for integrating the requisite spiking intrinsic into the accelerator fabric itself. Additionally, INNAT works together with TUDelft in developing the spiking neural network models that are deployed atop the accelerator for inference.

4.2.5 Demonstrator architecture

SCD 6.2.A:

SCD 6.2.A demonstrator can be split into four key levels: Sensor level, Verification level, Control and processing level and Interfacing level. In this section, we will outline more details for each of this part of the demonstrator. A block diagram of the demonstrator is depicted in **Error! Reference source not found.**:

- Sensor level
This part consists of multiple heterogeneous sensors which will be sensing the environment around the platform, e.g., automotive mmWave radar (77GHz, 24GHz, etc.), RGB video camera, DVS (Dynamic Vision Sensor) camera and others. Each of these sensors introduces various sensor modalities, each of which is useful for a particular application, they have further various types of interfaces and abilities to do a pre-processing of their raw output data. These possibilities are important to consider for a distributed computation approach, i.e., whether it is more efficient to do raw sensor data pre-processing at the sensor level or at a specialised accelerator level. The depth of pre-processing is done at the Control and processing level depending on the application, computation and power requirements.
Sensor level further interfaces with a Verification level through its several sub-blocks.
- Verification level
This level encapsulates two main sub-blocks: Sensor verification and Data Verification. As sensors can physically degrade over time, the quality of the received data, therefore degrades too. This can be checked at the Sensor verification stage. From a pure software architecture point of view, there is very little that can be done about this. Problems like these, however, are detected at the algorithmic level. E.g., noise level and signal-to-noise level measurements are used to detect certain types of signal degradation. Other options could include cross-correlation of signals between different sensors. E.g., if one sensor misses a signal that is detected by other sensors, this is an indication that this sensor is malfunctioning.

Data Verification block is targeting fail-robustness aspects like data integrity, capacity problems and excessive latency issues. At this stage, data is verified that the received data is not altered and is complete if it is consistent and there are no missing packets and finally if there is a deadlock situation when the processing pipeline is waiting indefinitely for data to arrive from different sensors.

- Control and processing level

This level is responsible for providing a general system control as well as the key processing system capabilities, which include a dedicated neuromorphic accelerator block and a general-purpose microprocessor core. In the block diagram (**Error! Reference source not found.**) we also outline the internal structure of the neuromorphic accelerator block, which will be an essential part of this demonstrator.

- Interfacing level

Finally, there is an interfacing level of the system. There are various possibilities for this level depending on the final application requirements. This level could output if needed, signals to actuators at higher levels, it could further communicate with users by means of GUI to demonstrate the current status of processing or warnings from the verification level, etc.

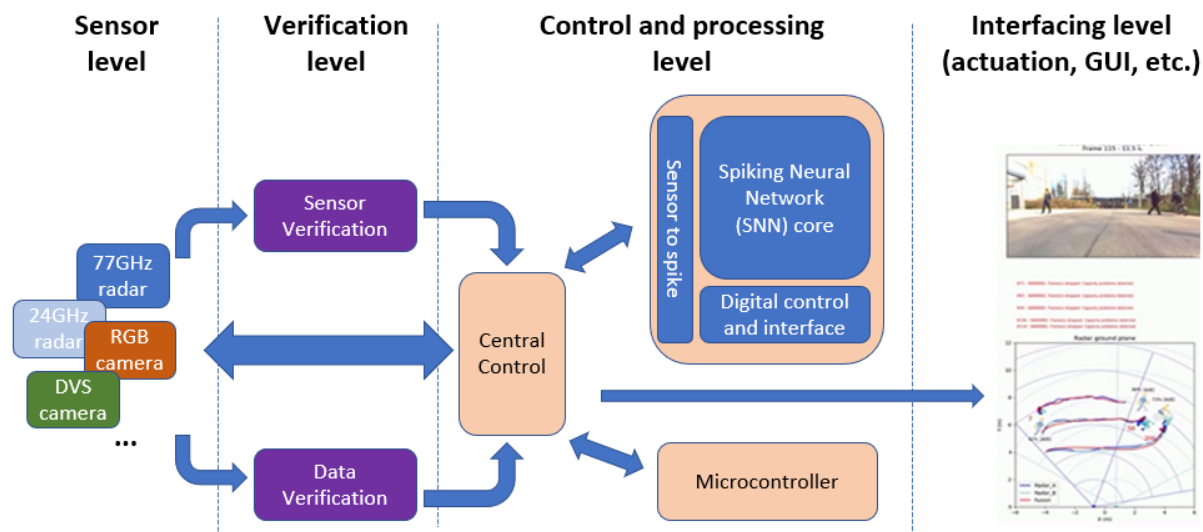


FIGURE 12: MULTILEVEL APPROACH OF THE SYSTEM ARCHITECTURE OF SCD 6.2.A DEMONSTRATOR

SCD 6.2.B:

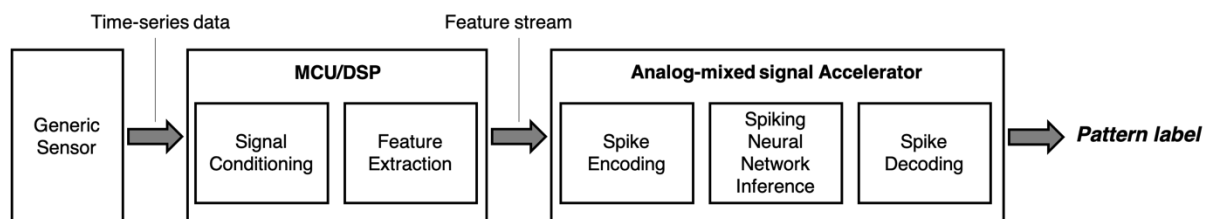


FIGURE 13: SYSTEM ARCHITECTURE OF SCD 6.2.B DEMONSTRATOR

Demonstrator 6.2.B consists of three stages: sensing, pre-processing on an MCU/DSP and inference on the analogue-mixed signal accelerator. For the demonstration, the sensor will be emulated by a

synthetic data trace injected from a PC. This trace consists of a time-series data stream with embedded temporal patterns, e.g., of anomalous behaviour in the powertrain. In the second stage, the raw time-series data stream is injected into an MCU/DSP where it is conditioned to amplify relevant features and suppress noise. Subsequently, signal processing steps are executed to extract the relevant features which enable the detection and identification of patterns within the stream. Commonly this involves operations such as FFTs to decompose samples into frequency bins for characterisation. The resulting stream represents a sequence of feature vectors that may not be processed by a spiking neural network (SNN) model. In the third stage, the vectors are encoded into a spike representation that enables their processing by an SNN. This is performed by dedicated computing blocks within the accelerator. The spike encoded vectors are then injected into the accelerator fabric configured to execute the trained SNN model. Inference is carried out in an event-driven fashion inside the accelerator – i.e., inference only occurs when the accelerator is stimulated with spike encoded data. The SNN subsequently produces a stream of spike events at one or more neurons corresponding to a specific pattern label. This stream is decoded using a specific decoding algorithm, facilitating the classification of the detected pattern.

4.2.6 Requirements

TABLE 10: #1 FR SCD 6.2

| | #1 Functional Requirements / FR |
|--------------------------------------|--|
| ID | AI4CSM_SC6_D2-7 |
| FR Naming | Efficiency of road user classification. |
| Definition of FR | Classification of road users and cars based on multi sensors data. |
| Description of FR | The AI-based processing shall classify road users based on heterogeneous sensor information. |
| What is measured: | Perception precision |
| KPI | Quantitative [%] |
| Method of collection and measurement | Road users and cars will be observed, and raw sensor data will be recorded by a multi sensor setup. Further, this data will be fed into the developed classification processing chain, which will be initially trained on a subset of these recordings and later inferenced to measure the accuracy of target classification |
| Target Value | Multi target and multi type classification of road users. |
| Verification and validation method | Accuracy $\geq 70\%$. |

TABLE 11: #2 FR SCD 6.2

| | #2 Functional Requirements / FR |
|------------------|---|
| ID | AI4CSM_SC6_D2-8 |
| FR Naming | Time-series pattern recognition |
| Definition of FR | Ability to recognise a time-series pattern of a pre-determined length in the sensor data stream |

| | |
|--------------------------------------|---|
| Description of FR | The neuromorphic processing system shall be able to detect and classify time-series patterns in sensor data streams |
| What is measured: | Pattern recognition accuracy |
| KPI | Quantitative (%) |
| Method of collection and measurement | The SNN model is trained using synthetic and real-data captured from sensors. The testing accuracy of the model is determined in a simulation environment, and the latency between presentation of the data sample and read-out of the inference result is measured. The same procedure is repeated on hardware for verification. |
| Target Value | >90% detection accuracy for the selected fault condition |
| Verification and validation method | Simulation and hardware validation |

TABLE 12: #3 FR SCD 6.2

| | #3 Functional Requirements / FR |
|--------------------------------------|--|
| ID | AI4CSM_SC6_D2-9 |
| FR Naming | Always-on inference |
| Definition of FR | Functional availability |
| Description of FR | The inference function shall be available continuously |
| What is measured: | Functional availability |
| KPI | Qualitative – achieved/not-achieved |
| Method of collection and measurement | Simulation of the processing pipeline, subsequent validation on the hardware platform |
| Target Value | Demonstrate always-on detection of patterns in the sensor data |
| Verification and validation method | Availability of the processing platform for inference when sensor data becomes available |

TABLE 13: #1 NFR SCD 6.2

| | #1 Non-Functional Requirements / NFR |
|--------------------------------------|--|
| ID | AI4CSM_SC6_D2-10 |
| NFR Naming | Expandability of NN accelerator |
| Definition of NFR | Adaptability of NN accelerator for future system and application modifications. |
| Description of NFR | Developed neuromorphic accelerator, and its platform are capable of dealing with modifications and extensions in the system & application levels. |
| What is measured: | Over the project lifetime, the final system and application will be continuously developed, improved and extended, therefore the designed accelerator and its architecture should support these modifications. |
| KPI | Achieved / Not Achieved |
| Method of collection and measurement | Introduce modifications and extension into the system and application that would affect its mapping into the accelerator. |

| | |
|------------------------------------|---|
| Target Value | Evaluation platform for the demonstrator and NN accelerator architecture are tolerant to application extensions. |
| Verification and validation method | Possibility to reuse developed neuromorphic accelerator for modifications and extensions in final system and application. |

TABLE 14: #2 NFR SCD 6.2

| | #2 Non-Functional Requirements / NFR |
|--------------------------------------|---|
| ID | AI4CSM_SC6_D2-11 |
| NFR Naming | Inference latency |
| Definition of NFR | Mean response time |
| Description of NFR | Monitoring function shall recognise fault conditions rapidly |
| What is measured: | The time between pre-processed sensor data being offered to the inference platform and an inference result becoming available |
| KPI | Quantitative (seconds) |
| Method of collection and measurement | Testing of the trained model in a simulation environment |
| Target Value | Inference latency for the demonstration shall be within 10ms |
| Verification and validation method | Comparison of hardware measurement against simulation model |

TABLE 15: #3 NFR SCD 6.2

| | #3 Non-Functional Requirements / NFR |
|--------------------------------------|--|
| ID | AI4CSM_SC6_D2-12 |
| NFR Naming | Inference power dissipation |
| Definition of NFR | Monitoring function shall consume a minimal amount of power |
| Description of NFR | The power consumed by the platform in performing inference on the trained neural network model for time-series pattern recognition |
| What is measured: | Power dissipation |
| KPI | Quantitative (Watts) |
| Method of collection and measurement | Measurement and characterisation of the hardware platform |
| Target Value | Inference power dissipation for the selected demonstration shall be under 10mW |
| Verification and validation method | Comparison against simulation results |

4.2.7 Validation, verification, and testing

SCD 6.2.A:

- **Verification:** The accuracy of the models for detection, tracking and classification of VRU will be evaluated based on the dataset collected from real live use cases and used during the

development process. Furthermore, the inference latency will be measured on the target accelerator architecture.

- **Validation:** System deployment and algorithms inference in a real live environment with multiple pedestrians, cyclists and conventional vehicles will be implemented, measured and evaluated. Moreover, inference latency will be calculated, and average power consumption for a particular use case will be measured and analysed.

SCD 6.2.B:

- **Verification:** The development of the spiking neural network models will utilise test data
- **Validation:** System deployment and algorithms inference in a real live environment with multiple pedestrians, cyclists and conventional vehicles will be implemented, measured and evaluated. Moreover, inference latency will be calculated and average power consumption for a particular use case will be measured and analysed.

4.3 SCD 6.3 - Affordable AI-enabled perception

In SCD 6.3, the partners plan to integrate AI-enabled perception and sensor fusion platforms technologies into a local demonstrator for a use case for delivering goods (last-mile delivery) into a controlled urban/sub-urban environment. The perception and sensor fusion platform will use multiple perception sensors, AI-based processing techniques/methods, V2X communication technology and focus on optimisation for a low cost. Figure 14 summarise the demonstrator in a four-quadrant view. (ECAS: Electric, connected, automated and shared)

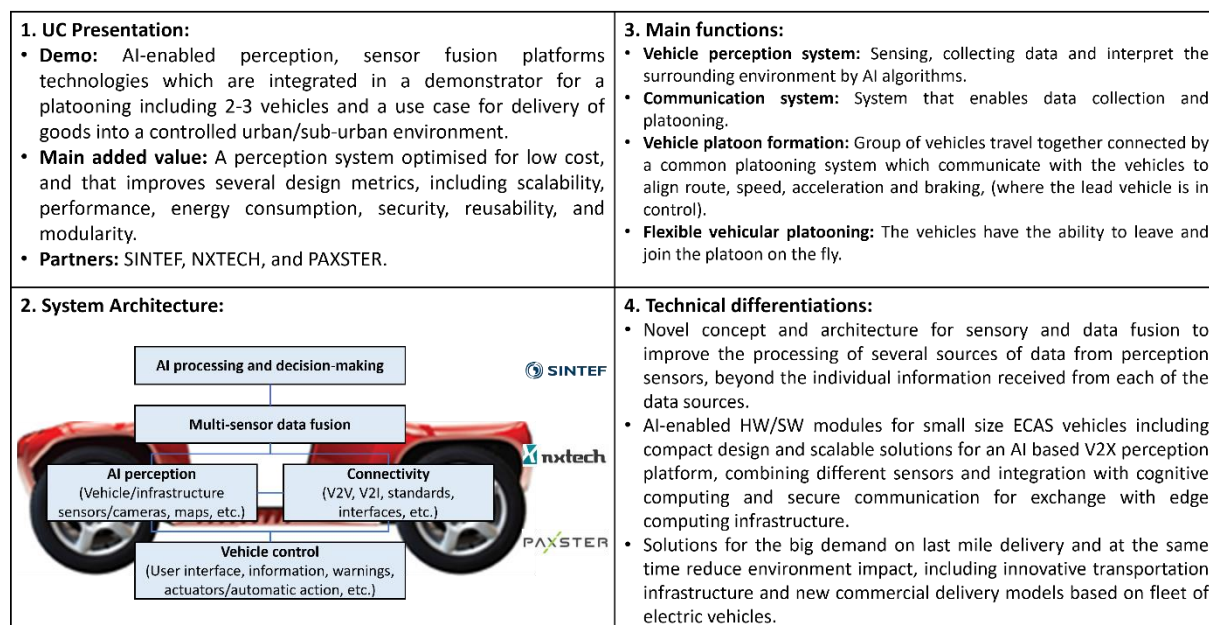


FIGURE 14: SCD 6.3 OVERVIEW

4.3.1 Demonstrator description

Figure 15 illustrates the SCD 6.3 demonstrator use case overview, and the demonstrator's key development steps are:

- Novel concepts and architecture for sensory and data fusion improve the processing of several data sources from perception sensors beyond the individual information received from each data source.
- AI-enabled HW/SW modules for small ECAS vehicles include the compact design and scalable solutions for an AI-based V2X perception platform, combining different sensors and integration with cognitive computing and secure communication for exchange with edge computing infrastructure.
- Solutions for the increased demand for last-mile delivery while reducing environmental impact include innovative transportation infrastructure and new commercial delivery models based on platooning and fleet management of electric vehicles.

The primary focus of the activities is to evaluate and develop a perception system concept optimised for low cost and improve several design metrics, such as scalability, performance, energy consumption, and modularity.



FIGURE 15: SCD 6.3 DEMONSTRATOR USE CASE OVERVIEW

The SCD 6.3 concept overview is illustrated in Figure 16, facilitating perception of the surroundings, multi-sensors and connectivity, fleet and route control, and motion control. AI-enabled perception, sensor fusion platforms technologies to be integrated into a local demonstrator for a platooning (2-3 PAXSTER vehicles) use case for delivery of goods into a controlled urban/sub-urban environment. Perception and sensor fusion platform using multiple perception sensors (e.g., camera, LiDAR, etc.) and AI-based processing techniques and methods. Platform interfaces are needed to integrate Ethernet 100M/1G/10Gbps, SFP+, 8 x 100BASE-T1, CAN-FD, cameras, ASIL-B computes, automotive interfaces with vision acceleration and ASIL-D subsystem.

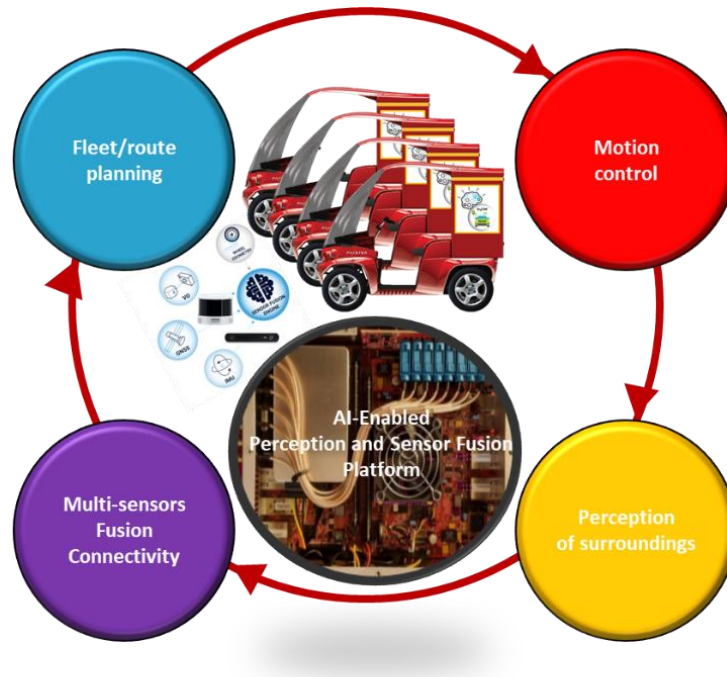


FIGURE 16: SCD 6.3 CONCEPT

4.3.2 Objectives

The main objectives for the SCD6.3 demonstrator are:

- Develop a novel concept for perception platform, sensor fusion techniques and architecture to improve perception systems and integration in a new niche market for small, low-cost autonomous vehicles.
- AI-enabled HW/SW modules for small ECAS vehicles using perception and sensor fusion modules for automated electrical and connected vehicles.
- Concepts for small size vehicles with autonomous functions and perception capabilities to alleviate the strain on existing delivery services and create new business opportunities for mobility services targeting the delivery of goods.
- Demonstrator for test and validation. AI-enabled perception, sensor fusion platform technologies integrated into a demonstrator including 2-3 vehicles and a use case for delivery of goods into a controlled urban/sub-urban environment.

4.3.3 Alignment to the project and SC6 objectives

The following overall project objectives are addressed in demonstrator SCD 6.3:

- **O3 - Design silicon for deterministic low latency and build AI-accelerators for decision and learning:** Use of AI-accelerators for perception systems.
- **O4 - Solve complexity by trustable AI in functionally integrated systems:** Evaluation of trustable AI solutions in functionally integrated systems.
- **O5 - Design functional integrated ECS systems:** Evaluation and design functional integrated ECS for perception and sensor fusion.

The following WP1 objectives are addressed in demonstrator SCD 6.3:

- **O1.1 - Requirements and Specifications of Components:** Defining the requirements and specifications of HW components like perception sensors, processing units, and communication modules, plus necessary inherent interface standards and programming protocols/tools. Benefit and cost analysis will also be carried out.
- **O1.2 - Requirements and Specifications of Subsystems:** Defining the requirements and specifications of the sensor fusion, data interpretation, communication, planning, and cognitive decision-making subsystems, together with the interfaces among the individual subsystems to ensure seamless integration and reliable operation of the system. Address the subsystems' safety and security issues for the demonstrator.
- **O1.3 - Requirements and Specifications on Vehicle Level:** Defining the requirements and specifications of the low-cost small electric vehicle (level of automation vs driver support, braking system, navigation system, energy efficiency, vehicle range, load capacity, production costs, etc.).
- **O1.4 - Requirements and Specifications for Vehicle Operation in Mission Environment:** Defining the requirements and specifications regarding the solution to the increased demand for last-mile delivery and reducing environmental impact, including innovative transportation infrastructure and new commercial delivery models based on a fleet of electric vehicles. In addition, for test and validation, define the use case scenarios on flexible vehicular platooning and delivery of goods, where the vehicles can leave and join the fleet on the fly.

The following SC6 objectives on system level are addressed in demonstrator SCD 6.3:

- **SC6-O1 - Develop a platform framework to address scalability, functional integration, virtualisation, optimisation, software-defined functions by sharing computing resources and connectivity through the fusion of information. Enable load specific and optimised sharing of computing resources composed of a mixture of single- or multi-core CPUs, accelerators, GPUs, FPGAs, NNs, neuromorphic processors, etc.:** Development platform to include perception and acceleration solutions using 2 x 32-bit CPU, 8x ARM cores, Computation Cores – Quad ARM, vision processing and acceleration on-chip image signal processor (ISP), integrated GPU.
- **SC6-O2 - The platform framework approach involves distributing intelligence to the perception sensors to facilitate local processing of raw sensor data and implementing a hybrid distributed system architecture that optimises latency, share the computing resources at the deep edge where data is pre-processed, reducing bandwidth requirements, power consumption, expensive cooling systems etc.:** Combination of Automotive Computer Vision Processor, High Performance Processor, ASIL-D Microcontroller.
- **SC6-O3 - Define the interfaces and communications protocols and topology for optimally and efficiently shared data and information in a distributed automotive functional domains environment to achieve improved acquisition and perception capabilities for harsh weather and challenging environmental conditions as well as dynamic situations including unexpected objects:** 2x CAN-FD (Flexible Data Rate) with enhanced payload.
- **SC6-O4 - Standardisation addressing:**
 - Standardisation activities targeting autonomous vehicles and the perception, sensor fusion AI and safety (e.g., ISO/PAS 21448 (SOTIF).
 - Safety of the intended functionality, ISO 26262 aims at mitigating risk due to system failure.
 - Road vehicles - Safety and cybersecurity for automated driving systems - Design, verification, and validation (ISO/TR 4804:2020 -> ISO/AWI TS 5083).

- Functional safety for V2V cooperative functions, etc.).

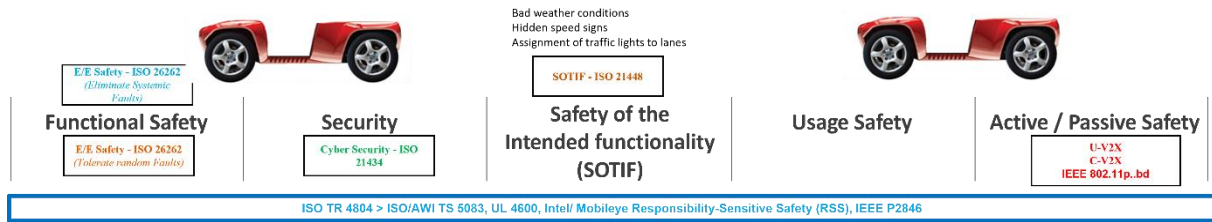


FIGURE 17: STANDARDS RELEVANT TO SCD 6.3 DEMONSTRATOR

The following SC6 objectives on subsystem level are addressed in demonstrator SCD 6.3:

- **SC6-06 - Prototype and validate the developed concepts and designs in silicon and demonstrate their value for automation of safety-critical systems through increased functional integration:** Prototype and validate the developed concepts and designs.
- **SC6-07 - Develop low-power high-cognition sensors and systems for computationally cheap (cost-efficient) and instantaneous scene interpretation:** Evaluation and development of systems for cost-efficient perception and sensor fusion.
- **SC6-08 - Provide next generation cognitive sensor hardware and embedded software solutions enabling enhanced and instantaneous scene interpretation while minimising its local power consumption and optimising its computational resources/approach:** Embedded HW/SW solutions for optimising computational resources.

4.3.4 Partners and their role

The main cooperating partners in this demonstrator complement each other. SINTEF represents the research and development (R&D) sector, NXTECH representing the small and medium-sized enterprise (SME) sector, and PAXSTER representing the original equipment manufacturer (OEM) sector, as illustrated in Figure 18.

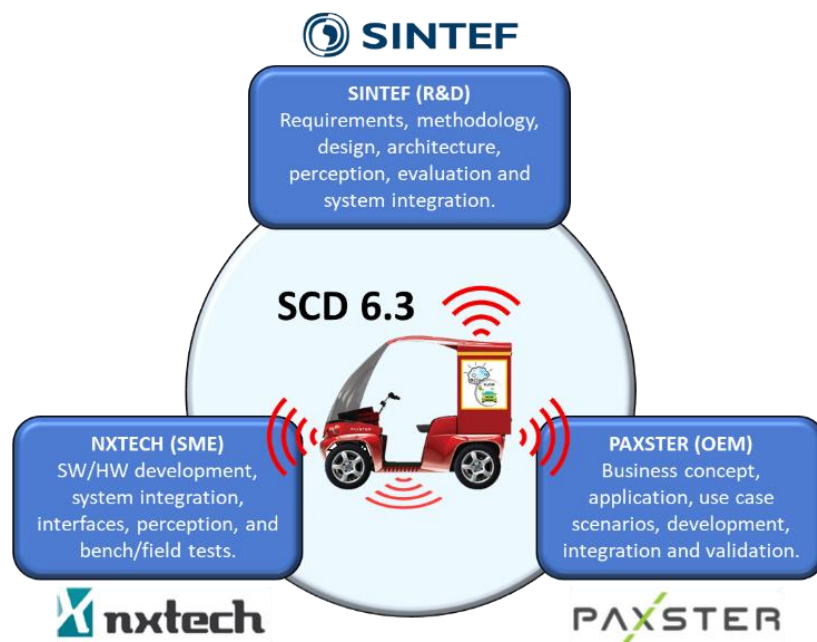


FIGURE 18: SCD 6.3 PARTNERS AND THEIR MAIN ROLES IN THE DEMONSTRATOR DEVELOPMENT

This deliverable is an outcome of the work carried out in task T1.6, and the partners' main roles are:

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SINTEF's role is to define and develop the technical requirements and specifications for evaluating and implementing compact, energy efficient and cost-effective perception sensors, together with sensor fusion techniques and AI-based platforms integrated into the small-size electric and connected vehicles. The work also includes standardisation activities for reliable and safe autonomous driving, including perception and sensor fusion functions.

PAXSTER is defining the high-level requirements and specifications for the perception sensors, sensor fusion techniques and the HW/SW platform for the vehicle's application scenarios. Focus is on the definition of the requirements and specifications of local demonstrator for platooning and fleet management use case scenarios for delivery of goods into a controlled urban/sub-urban environment.

NXTECH is defining the technical requirements and specifications of the electronics and components for the communication, perception sensors, and sensor fusion techniques to be integrated into the vehicles; and identifying the design trade-off for the integration of the electronics, communication, and components for perception modules.

4.3.5 Demonstrator architecture

Development platform including perception and acceleration solutions:

- Vision: Front Camera and embedded HW/SW.
- LiDAR: Solid State Lidar and 360 Mechanical Lidar and embedded HW/SW.
- IMU and Integrated GNSS.
- OS - Linux Ubuntu ++.
- Middleware: ROS (Robot Operating System).
- DNN Accelerator Card using Massively Parallel Processor Array (MPPA) high performance AI accelerator.

Figure 19 gives an overview of the functional blocks in the vehicle that will be used for demonstration in SCD 6.3.

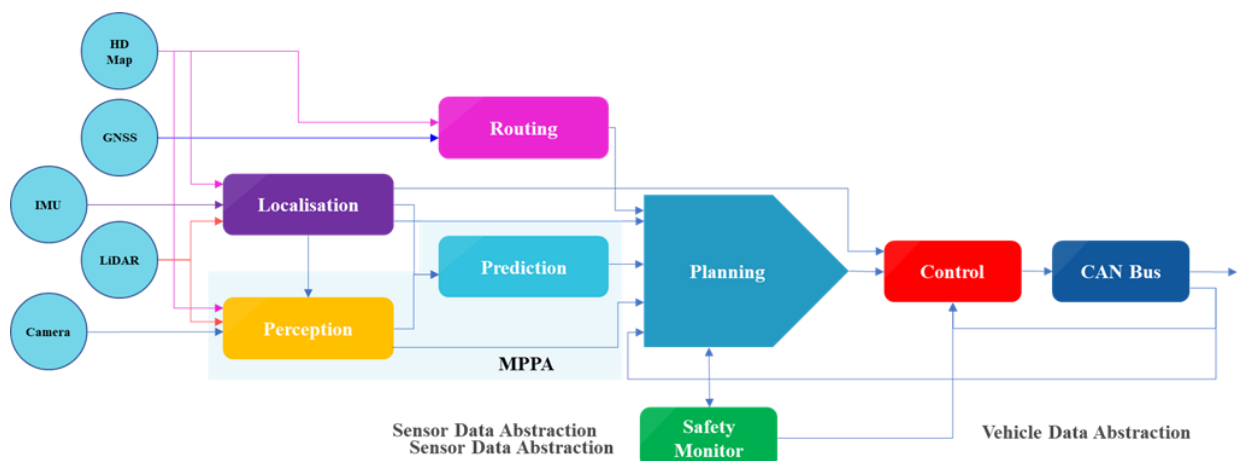


FIGURE 19: OVERVIEW OF THE FUNCTIONAL BLOCKS IN THE VEHICLE USED FOR DEMONSTRATION

Figure 20 gives an overview of drive-by-wire in vehicle implementation today, while Figure 21 illustrates the next step development of functional blocks planned in the vehicles used for demonstration. Project focuses are on the perception domain, platform development and embedded solutions (orange boxes) together with seamless integration through interfaces and communication.

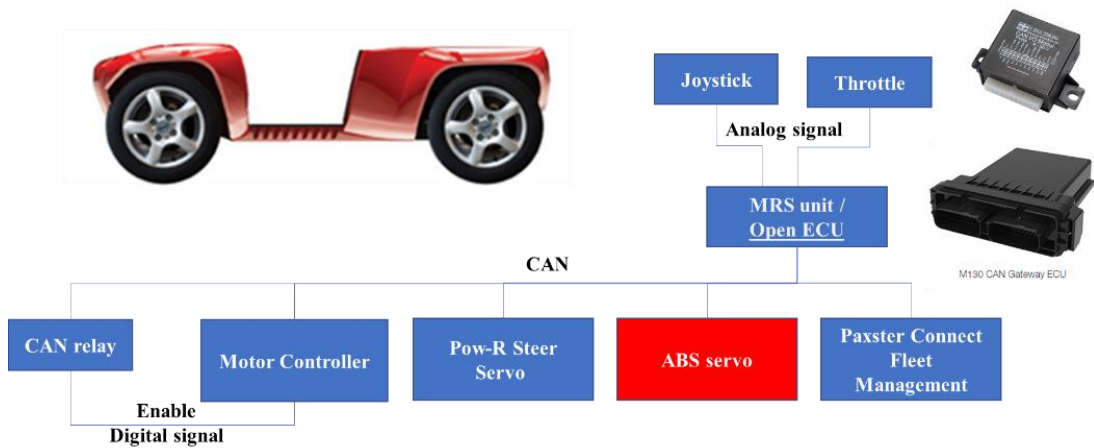


FIGURE 20: DRIVE-BY-WIRE IN VEHICLE IMPLEMENTATION TODAY

The initial design includes the basic function for the vehicle that will be enhanced with the integration of a perception domain platform that includes perception and acceleration capabilities. A new embedded development is added to the architecture to support the integration and experimentation with various perception sensors to be used (IMU, camera, LiDAR) as presented in Figure 21.

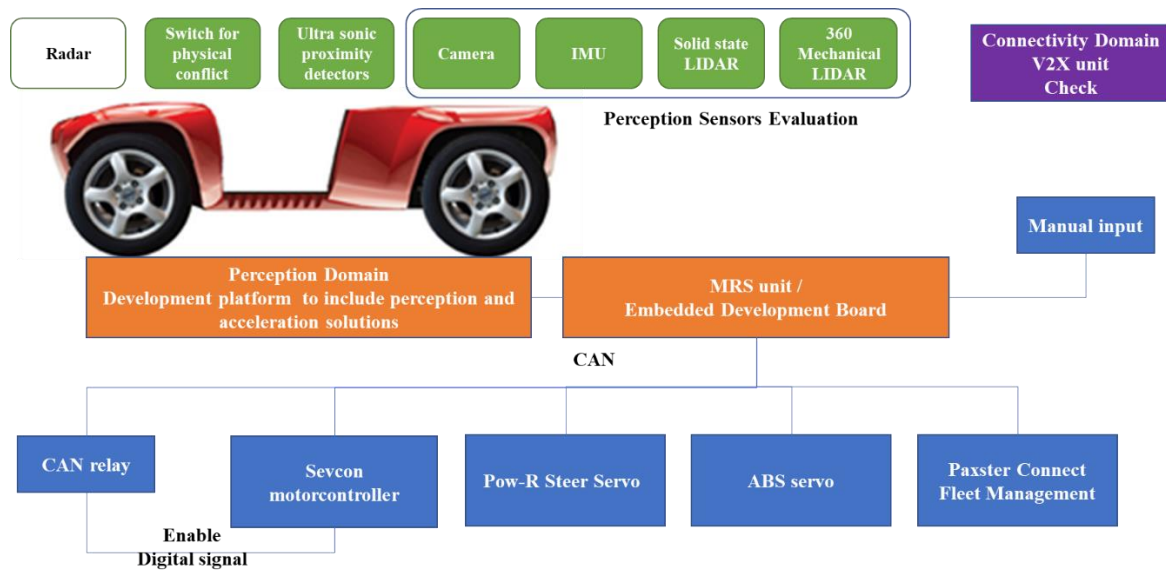


FIGURE 21: NEXT STEP DEVELOPMENT OF THE FUNCTIONAL BLOCKS IN THE VEHICLES USED FOR DEMONSTRATION

4.3.6 Requirements

TABLE 16: #1 FR SCD 6.3

| #1 Functional Requirements / FR | |
|---------------------------------|--|
| ID | AI4CSM_SC6_D3-13 |
| FR Naming | Vehicle position accuracy. |
| Definition of FR | Ability to estimate exact positioning of vehicles. |
| Description of FR | Vehicle accuracy estimation. |
| What is measured | Position deviation. |
| KPI | Quantitative [m]. |

| | |
|--------------------------------------|---|
| Method of collection and measurement | Platoon measurement simultaneously with a reference vehicle. |
| Target Value | < 1 m deviation for vehicle speed 45 km/h. |
| Verification and validation method | Relative position to a reference vehicle at different speeds. |

TABLE 17: #2 FR SCD 6.3

| | #2 Functional Requirements / FR |
|--------------------------------------|---|
| ID | AI4CSM_SC6_D3-14 |
| FR Naming | Camera perception algorithms. |
| Definition of FR | Ability to identify objects in the vehicle surroundings. |
| Description of FR | Pattern and object recognition precision and perception parameters precision. |
| What is measured | Recognise specific vehicle surrounding environment in real-time (time defined). |
| KPI | Quantitative [%]. |
| Method of collection and measurement | Pattern and object recognition measurement during platoon operation. |
| Target Value | AI model accuracy $\geq 70\%$ for specific object. |
| Verification and validation method | Object recognition algorithm precision. |

TABLE 18: #3 FR SCD 6.3

| | #3 Functional Requirements / FR |
|--------------------------------------|--|
| ID | AI4CSM_SC6_D3-15 |
| FR Naming | Vehicle platooning scalability. |
| Definition of FR | The ability to scale up or down the system (users, functionalities, modules, components, etc.); in our case vehicles in the platoon. |
| Description of FR | Vehicle platooning scalability (connect/disconnect vehicles in the platoon). |
| What is measured | Seamlessly connect and disconnect vehicles in the platoon. |
| KPI | Quantitative [#]. |
| Method of collection and measurement | Measuring the number of vehicles that are automatically connected and disconnected to the platoon correctly/safely. |
| Target Value | Up to 3 vehicles in the platoon. |
| Verification and validation method | Correctly/safely increase the platoon from 1 to 3 vehicles, and then decrease the platoon from 3 to 1 vehicles. |

TABLE 19: #1 NFR SCD 6.3

| | #1 Non-Functional Requirements / NFR |
|----|---|
| ID | AI4CSM_SC6_D3-16 |

| | |
|--------------------------------------|---|
| NFR Naming | Reliability (Maturity). |
| Definition of NFR | <p>Reliability is the degree to which a system, product or component performs specified functions under specified conditions for a specified period (ISO/IEC 25010). The relevant sub-characteristic is maturity. That is the degree to which a system, product or component meets needs for reliability under normal operation.</p> <p>Reliability is the capability of the affordable AI-enabled perception system to maintain its level of performance under the mission, road and environmental conditions stated (Operational design domain - ODD). Maturity of the AI-enabled perception system is the capability to avoid failures as the result of faults in HW/SW, AI algorithms and to reduce the frequencies of these possible failures. Maturity reflects the degree of reduction in frequencies of failures (compared to the non-mature version at the beginning of the project).</p> |
| Description of NFR | Comparing the perception parameters at the beginning and the end of the project. |
| What is measured | Maturity: Perception parameters. |
| KPI | AI-enabled perception precision increase. Quantitative [#]. |
| Method of collection and measurement | Data logging and database historian through demonstrator evaluation (perception detection and sensor fusion). |
| Target Value | ≥ 10% of improvements of the perception measurement accuracy for different road conditions. |
| Verification and validation method | Perception parameters comparison. |

TABLE 20: #2 NFR SCD 6.3

| | #2 Non-Functional Requirements / NFR |
|--------------------------------------|--|
| ID | AI4CSM_SC6_D3-17 |
| NFR Naming | Compatibility (Interoperability). |
| Definition of NFR | Degree to which a product, system or component can exchange information with other products, systems, or components and/or perform its required functions while sharing the same hardware or software environment. |
| Description of NFR | How efficient will the connectivity/AI modules contribute to performing and improving the capability to exchange information with other units (products, systems, components) by compatibility functions (Coexistence, interoperability). |
| What is measured | Interoperability: Connectivity/AI functions compatibility. |
| KPI | Connectivity/AI compatibility functions. Qualitative [%]. |
| Method of collection and measurement | Demonstrator evaluation: Fleet-based delivery of goods. |
| Target Value | 10 % Compatibility improvement based on connectivity/AI functions compared with the start of the project. |
| Verification and validation method | AI models use 2 to 4 APIs for communicating with different data sources. |

TABLE 21: #3 NFR SCD 6.3

| | #3 Non-Functional Requirements / NFR |
|--------------------------------------|--|
| ID | AI4CSM_SC6_D3.18 |
| NFR Naming | Maintainability (Testability). |
| Definition of NFR | Degree of effectiveness and efficiency with which a product or system can be modified to improve it, correct it, or adapt it to changes in environment, and in requirements (ISO/IEC 25010). |
| Description of NFR | How efficient will the AI modules contribute to performing and improving the capability to adapt changes and new needs by maintainability functions (modularity, reusability, analysability, modifiability, testability). |
| What is measured | Testability: AI functions maintainability. |
| KPI | AI maintainability functions. Qualitative [%]. |
| Method of collection and measurement | Demonstrator evaluation: Fleet-based delivery of goods. |
| Target Value | 15 % maintainability improvement based on AI functions compared with the start of the project. |
| Verification and validation method | New models can be tested initially by a test-file before deployment. Models can be updated remotely. Models can be versioned. |

4.3.7 Validation, verification, and testing

The validation, verification and testing process will take place in several steps during experimental demonstrations in real environment, facilitating the functional requirements regarding relative positioning to a reference vehicle at a different speed, object recognition algorithms precision, and increasing and decreasing vehicles safely in a platoon. For the non-functional requirements regarding reliability/maturity, compatibility/interoperability, and maintainability/testability, we will to a somewhat greater extent, rely on comparisons and evaluations.

The vehicles drive in a fleet over an area having the AI-enabled perception system making the measurements simultaneously with a reference vehicle. The reference vehicle read the surrounding perception information. The comparison between the two measurements will be made to guarantee the perception and positioning accuracy.

4.4 SCD 6.4 - Localisation and 3D mapping

Autonomous vehicles are currently isolated devices, using and relying on the inputs from their own sensors only. However, in some situations, it is valuable to have also “a different sight” of the current scene to understand it correctly and robustly. Vehicle isolation also leads to the situation when many same tasks are unnecessarily computed on each vehicle.

For those reasons, the **need for inter-vehicle sharing** is obvious, however, very large datasets must be transferred in a very short time. In order to fulfil this task, the **data bitrate has to be significantly reduced**.

The aim of this demonstrator is to reach the desired **bitrate reduction** using AI-based feature extraction, segmentation of clustering, followed by **intelligent inter-agent data sharing**, when only

the simplified and necessary information will be extracted from the raw sensor output instead of sharing all the data.

Another aim is to **protect the vehicle body** itself and the **humans around** it when it is stopped. The mapping of the nearest area of the vehicle will protect from damages and injuries, primarily during the door opening.

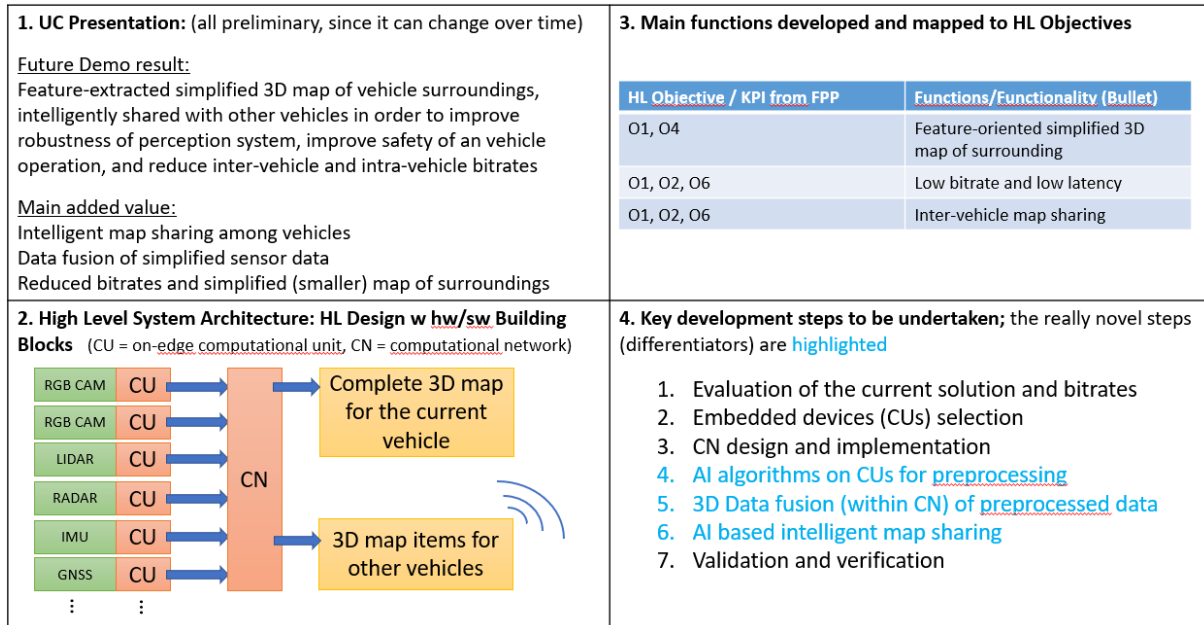


FIGURE 22: SCD 6.4 OVERVIEW

4.4.1 Demonstrator description

Demonstrator SCD 6.4 is dealing with two domains of localization and mapping within the surroundings of the car – the first and main area is focused on the 3D mapping during the vehicle movement in order to improve the navigation and safety during its operation at 4.4.1.1. The second task is focused to the nearest surroundings of the vehicle when it stops, protecting the vehicle body and the humans moving in the vicinity of vehicle at 4.4.1.2.

4.4.1.1 Shared 3D mapping of vehicle surroundings

The AI4CSM project follows up on the results from previous EU projects AutoDrive and NewControl. Within the AutoDrive project, the independent sensory frame has been developed, containing all the sensors which are employed in current autonomous vehicles. The main goal of this frame is to capture the data from real environment and log it into the dataset, which is further used for making the autonomous driving algorithms more robust. The NewControl project then mostly focused on AI-based data fusion and intelligent feature extraction, and object detection and classification. The original status of hardware after these two projects is shown in Figure 23.

In this project, we will follow up with this sensory frame, and we will focus on **bitrate reduction on the way from sensors to the computational units** in the first step. This will be reached by employing the on-the-edge computational units (CU) just behind the sensor, maintaining the signal pre-processing and initial feature extraction. We will also reduce a data flow by replacing the centralised computational unit with decentralised heterogeneous computational network (CN), composed on devices of different types suitable for specific tasks (CPUs, GPUs, etc.). Not all the data from the sensors

will be then transferred, and using the CN we reach the optimised data-flow spread as well. This approach is shown in Figure 24.

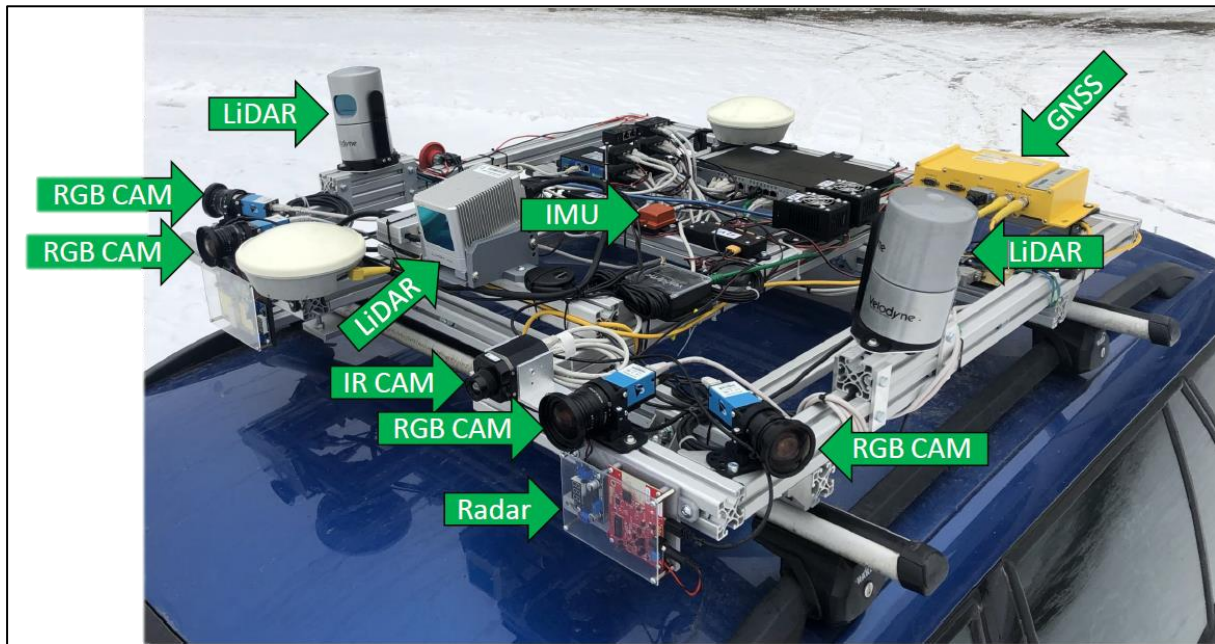


FIGURE 23: THE SENSORY FRAME DEVELOPED WITHIN PREVIOUS PROJECT ON THE BEGIN OF AI4CSM PROJECT.

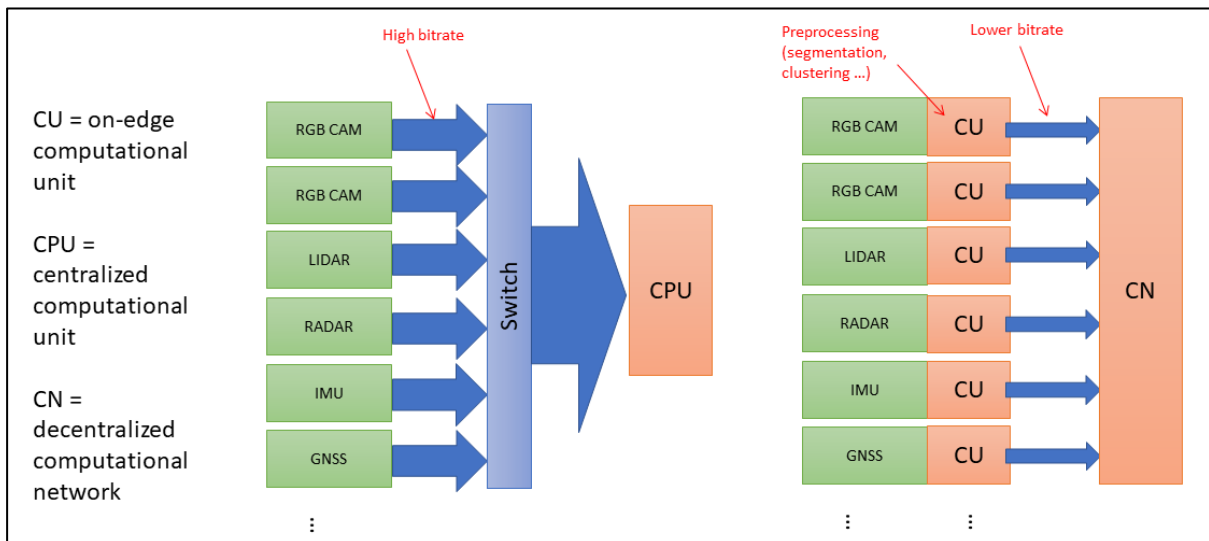


FIGURE 24 CURRENT HW ARCHITECTURE OF SENSORY FRAME (ON THE LEFT) AND PLANNED CHANGES WITHIN THE AI4CSM PROJECT

The next step after the intra-vehicle data-flow reduction is a development of algorithms for building and maintaining **feature-extracted simplified 3D map of vehicle surroundings** using multispectral data-fusion. It means that the surrounding map will be maintained as vectorised set of classified objects (e.g. vehicles, humans, ...) represented by class, shape and position; instead of currently used approaches with large memory footprint and complicated searching (e.g. occupancy grids).

Such a lightweight 3D map can be more easily wirelessly shared with other vehicles in the neighbourhood. The data-flow can be even more reduced by AI-based algorithms **sharing to another vehicle only the selected objects from the 3D map** relevant to its operation.

Such a 3D map sharing will improve the robustness of the perception system (the vehicles receives also another information, which is not able to gain by themselves – e.g. view behind the corner), improve the safety of an vehicle operation (“more eyes more see”) and reduce the inter-vehicle bitrate (the smaller the amount of data, the sooner it reaches the destination via the communication channel).

Such demo results will be reached by following steps; the really novel steps (differentiators) are highlighted in blue.

1. Evaluation of the current solution and current bitrates from sensors to CPU
2. Embedded on-the-edge devices (CUs) selection
3. Distributed heterogeneous computational network (CN) design and implementation
4. AI algorithms on on-the-edge CUs for pre-processing
5. 3D Data fusion of pre-processed (vectorized/simplified) data (within CN)
6. AI based intelligent inter-vehicle map sharing
7. Validation and verification in real environment

4.4.1.2 Near-field 3D mapping for safety purposes

The second domain is focused on the system and its components for the protection of the vehicle body or human moving in the vicinity of the vehicle. The new object & obstacle detection system for advanced vehicles using the sensor network, secure identification for object detection and recognition, will be presented. Recent sensor systems built on ToF cameras and ultrasonic or radar units will be developed. The detection system will serve for advanced car safety and driver assistance.

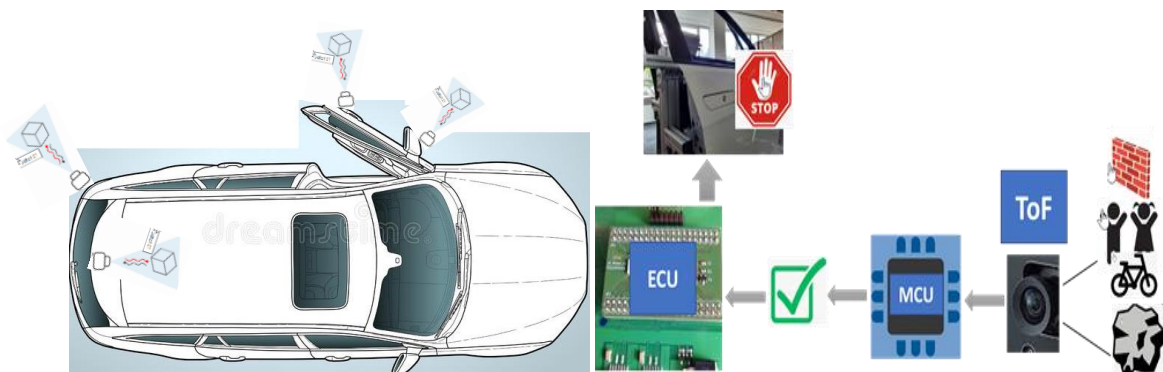


FIGURE 25 THE POTENTIAL AREAS OF COLLISION WHEN THE DOORS ARE OPENED (LEFT) AND THE SYSTEM OVERVIEW OF A TECHNICAL SOLUTION (RIGHT).

The motionless position of the vehicle is expected. The system should protect car doors, tailgate or hood when the opening/closing action is going on. The protection cases to demonstrate are avoiding collision car – human, car – static object (wall, ceiling, pole etc.). The system has to stop doors when the cases above come. The system will consist of the sensors that provide single or fused data, which are processed on the ECU, after processing and positive detection, the system produces an action, usually stop-action.

Within the demonstration, the whole object detection process and the toll chain will be presented.

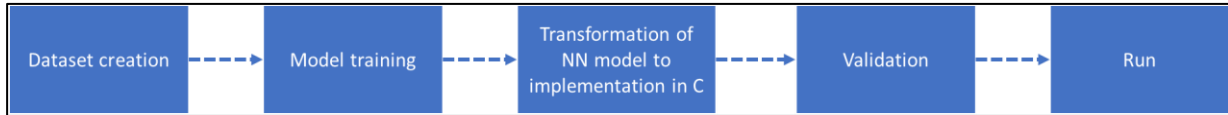


FIGURE 26: DETECTION PROCESS AND TOLL CHAIN

4.4.2 Objectives

The three main added values of this demonstrator are highlighted in bold in the previous text. All these three areas are not currently solved in autonomous cars and brings many abovementioned advances beyond the current State of the Art.

SCD6.4-O1: Inter-vehicle and intra-vehicle bitrate reduction

The goal is to lower bitrates from sensors to CUs, in order to deliver important information sooner and make the data-flow more efficient.

SCD6.4-O2: Feature-extracted simplified 3D map of vehicle surroundings

The lightweight vectorised 3D map of the surrounding occupies less space than traditional approaches and is then significantly easier to search, browse and it is faster to be shared among the vehicles.

SCD6.4-O3: Intelligent map sharing among the vehicles

Sharing of the map brings new angle of view which is unreachable by vehicle's own sensors, which improves robustness of perception system and improves safety of a vehicle operation. When the map is shared, it is also possible to estimate sensor failures and thus reach even more safe operations.

SCD6.4-O4: Protection of vehicle body and nearby humans during doors opening

Mapping the nearest surroundings of a vehicle while opening the doors will prevent damages of the vehicle itself but also prevent injuries to humans moving around the vehicle (e.g. collisions with bikers during door opening).

4.4.3 Alignment of the project and SC6 objectives

This demonstrator is contributing to following **overall project objectives**:

| Overall project Objectives | How the demonstrator contributes to this objective |
|---|--|
| O1: Develop Robust and Reliable Mobile Platforms | Inter-vehicle map sharing improves reliability and robustness of perception (O1). |
| O2: Develop Scalable and Embedded Intelligence for Edge Operation | Low bitrate and low latency are reached by embedded on-the-edge intelligence (O2). The nearest field mapping is maintained on the embedded system. |
| O4: Solve Complexity by Trustable AI in Functional Integrated Systems | Feature-oriented simplified 3D map of surrounding solves complexity of 3D maps (O4). |

Demonstrator SCD 6.4 is contributing to O1.2.: **Requirements and Specifications of Subsystems** from **WP1 objectives**.

This demonstrator is contributing to following **SC6 objectives**:

- Develop a platform framework to address scalability, functional integration, virtualisation, optimisation, software-defined functions by sharing computing resources and connectivity through the fusion of information. Enable load specific and optimised sharing of computing resources composed of a mixture of single- or multi-core CPUs, accelerators, GPUs, FPGAs, NNs, neuromorphic processors, etc.
- The platform framework approach involves distributing intelligence to the perception sensors to facilitate local processing of raw sensor data and implementing a hybrid distributed system architecture that optimises latency and share the computing resources at the deep edge where data is pre-processed reducing bandwidth requirements, power consumption, expensive cooling systems etc.
- Define the interfaces and communications protocols and topology for optimally and efficiently shared data and information in a distributed automotive functional domains environment to achieve improved acquisition and perception capabilities for harsh weather and challenging environmental conditions as well as dynamic situations, including unexpected objects.

4.4.4 Partners and their role

BUT: HW selection and network design, sensor data processing, AI algorithms, data fusion, 3D mapping, intelligent map sharing.

IMA: The nearest field mapping and the scene recognitions.

4.4.5 Demonstrator architecture

The demonstrator architecture is visualized in the Figure 27.

Each sensor is connected to the small low-power computational unit (CU), which is located at the same place as the sensor itself. Such a CU maintains basic feature extraction, segmentation or clustering. Only the results of these processes are transferred further to the computational network (CN), which is composed of more low-power devices of different types (CPUs, GPUs, ...). Such an approach allows using the most suitable hardware and software for every single task. Another advance is higher reliability, since failure of one device influences only few function, not the operation of whole system. The critical task can also be distributed over more devices.

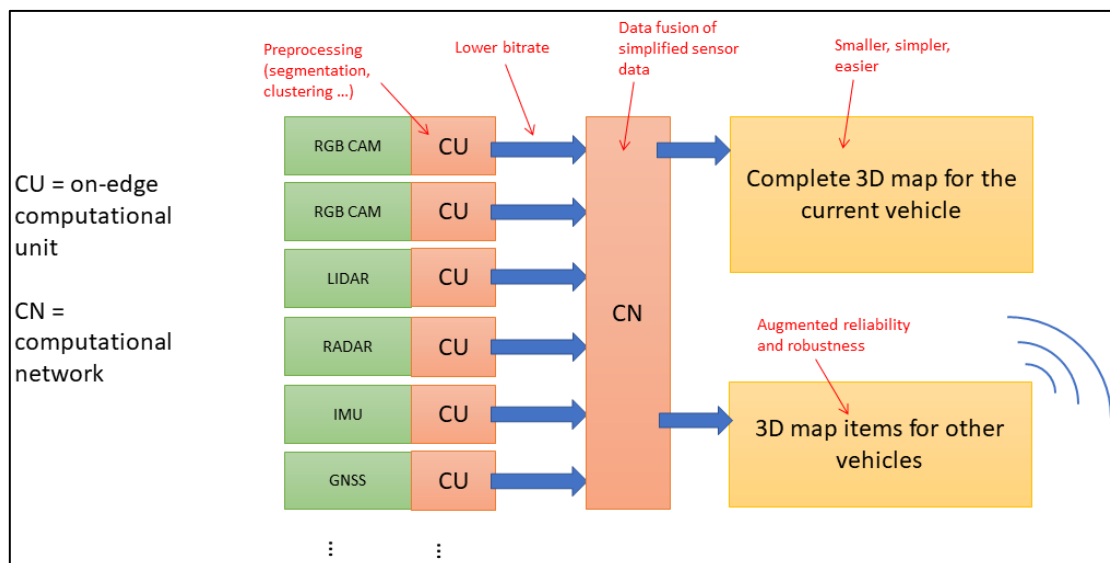


FIGURE 27: ARCHITECTURE OF THE DEMONSTRATOR SCD6.4

The near field demonstrator is depicted in the Figure 27 right. The architecture consists of:

- Sensor subsystem implemented in doors/trunk/frunk to secure the opening/closing action. ToF cameras, optionally ultrasound or radar sensors with image pre-processing are used.
- Electronic control unit acquiring the camera image, processing a running detection algorithm. Both AI and non-AI model to be validated.
- Communication subsystem to handle vehicle ecosystem resulting in actuation of doors, tailgate, hood.
- User interfaces, warning indicators.

4.4.6 Requirements

TABLE 22: #1 FR SCD6.4

| | #1 Functional Requirements / FR |
|--------------------------------------|--|
| ID | AI4CSM_SC6_D4-19 |
| FR Naming | Low intra-vehicle bitrates |
| Definition of FR | The sensor data are pre-processed on edge (in order to reduce bitrates from sensor to and within computational network). |
| Description of FR | Sum of all intra-vehicle bitrates will be examined. |
| What is measured: | Bitrate [Quantitative]. The bitrate on the way from sensors to the computational units |
| KPI | Overall Data Flow |
| Method of collection and measurement | The sum of bitrates on all data channels will be measured before and after developments within AI4CSM project. |
| Target Value | < 50% (the bitrate will be reduced at least to the half of original value) |
| Verification and validation method | Verification V1 |

TABLE 23: #2 FR SCD6.4

| | #2 Functional Requirements / FR |
|--------------------------------------|--|
| ID | AI4CSM_SC6_D4-20 |
| FR Naming | Feature-oriented 3D map |
| Definition of FR | The 3D map of vehicle surroundings is feature-oriented and simplified (vectorised), thus it is simple to browse and small in memory footprint. |
| Description of FR | The level of map simplicity will be assessed by memory footprint needed to store the map of surrounding without losing the relevant information. |
| What is measured: | Memory size [Quantitative]. The size of complete 3D maps of vehicle surroundings |
| KPI | Map Simplicity |
| Method of collection and measurement | The memory needed for saving the complete map of surroundings will be measured before and after developments within AI4CSM project. |
| Target Value | < 60% (the memory to store the complete map will be reduced at least by 40%) |
| Verification and validation method | Verification V2 |

TABLE 24: #3 FR SCD6.4

| | #3 Functional Requirements / FR |
|--------------------------------------|---|
| ID | AI4CSM_SC6_D4-21 |
| FR Naming | Inter-vehicle Map Sharing |
| Definition of FR | Relevant parts of a 3D map are shared among near vehicles (in order to improve robustness, safety, and reliability of a vehicle operation). |
| Description of FR | The vehicle is able to receive map items from other vehicles and update own map in real time. Thus, the vehicle will be “seeing” also features, which are not able to see by its own sensors. |
| What is measured: | Success ratio [Quantitative]. How many times the information from another vehicle enables the detection of a feature which will not be detectable by the own sensors only. |
| KPI | Augmented Map |
| Method of collection and measurement | The map augmentation using map items provided by other vehicles will be verified during the validation experiments. |
| Target Value | >90% (The vehicle is aware of more features than it is able to percept by its own sensors in 90% of cases when another vehicle is nearby). |
| Verification and validation method | Verification V3 |

TABLE 25: #1 NFR SCD6.4

| | #1 Non-Functional Requirements / NFR |
|------------|--------------------------------------|
| ID | AI4CSM_SC6_D4-22 |
| NFR Naming | Obstacle Detection Lag |

| | |
|--------------------------------------|--|
| Definition of NFR | The delay in the ability of the system to detect an unexpected obstacle. After the detection, the safety action will be triggered. |
| Description of NFR | The detection of the obstacle must be done in real-time. |
| What is measured: | Time [Quantitative]. The time between obstacle appearance and the corresponding safety event triggered. |
| KPI | Emergency Lag |
| Method of collection and measurement | Synchronised measuring of time of enabling the simulated obstacle and the time of triggering the emergency event. |
| Target Value | < 33 ms |
| Verification and validation method | The obstacle will be simulated in the sensor model at the time zero, and the time when the emergency event is triggered is measured. |

TABLE 26: #2 NFR SCD6.4

| | #2 Non-Functional Requirements / NFR |
|--------------------------------------|---|
| ID | AI4CSM_SC6_D4-23 |
| NFR Naming | Internal Delay |
| Definition of NFR | The delay between real event and its detection. |
| Description of NFR | The Internal delay caused by data pre-processing must not be longer than the delay at the original state when the data are processed simultaneously. |
| What is measured: | Time, relative [Quantitative]. The time between obstacle appearance and the corresponding event triggered after the project related to the value before the project. |
| KPI | Internal Detection Lag |
| Method of collection and measurement | Synchronized measuring of time of enabling the simulated obstacle and the time of object detection. |
| Target Value | <100% of the original internal lag |
| Verification and validation method | The delay between the simulated obstacle's appearance and its detection by the system will be measured at the beginning of the AI4CSM project and at the end of the project. The delays will be compared. |

TABLE 27: #3 NFR SCD6.4

| | #3 Non-Functional Requirements / NFR |
|--------------------|---|
| ID | AI4CSM_SC6_D4-24 |
| NFR Naming | Up-to-date 3D map |
| Definition of NFR | The ability of the 3D map to contain current state of environment, which is not older than given limit. |
| Description of NFR | The process of generating or updating of the 3D map of surroundings must be performed fast enough to fulfil the maximal age of information. |
| What is measured: | Time [Quantitative]. The time between change of the real environment and the corresponding change of the map. |

| | |
|--------------------------------------|---|
| KPI | Map Updating Lag |
| Method of collection and measurement | Synchronized measuring of time of enabling the simulated obstacle and its time of creation in the 3D map |
| Target Value | < 100 ms |
| Verification and validation method | The obstacle will be simulated in the sensors model at the time zero, and the time when the obstacle will appear on the map will be measured. |

4.4.7 Validation, verification, and testing

Several verification experiments will be performed:

- **V1: Overall Data Flow:** The sum of bitrates on all communication channels within the vehicle's perception system will be evaluated on current sensory frame and after the integration of a development reached within AI4CSM project.
- **V2: Map Simplicity:** The memory footprint needed for storing the complete map of surroundings will be evaluated on current sensory frame and after the AI4CSM project developments.
- **V3: Augmented Map:** The map sharing ability will be verified on semi-simulated experiment when two communicating vehicles will be simulated by time-shifting of two journeys of the single vehicle.
- **V4: Nearest-field detections:** The testing will be performed under support of automated test tool TESSY, acquired data for predictor validation, real data for detection process validation; in laboratory conditions, systems components tests one-by-one component, integrated system tests on real data; and in outdoor conditions, housing in progress, test description to be done.

4.5 SCD 6.5 - 3D Time of Flight with Aurix PPU

The demonstrator will show a perception subsystem, which will include novel 3D Time of Flight (ToF) camera sensor, a new network subsystem, a novel power management integrated circuit (PMIC) and a novel processing unit based on AURIX 3G + PPU.

Figure 28 shows the four-quadrant view of the demonstrator for a broader overview.

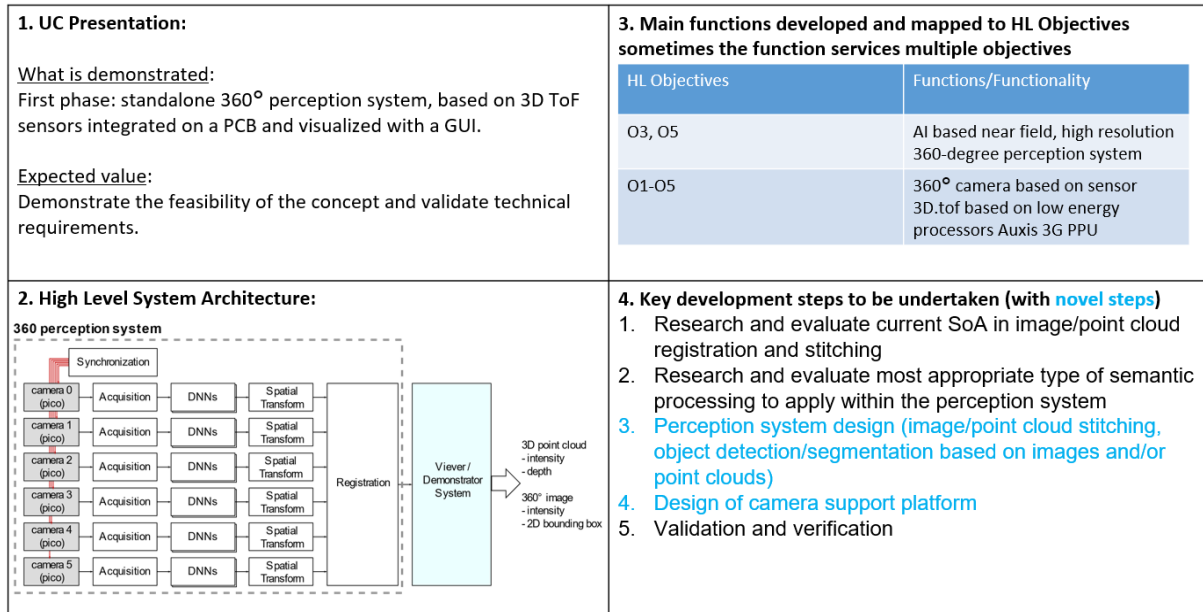


FIGURE 28: SCD 6.5 OVERVIEW

4.5.1 Demonstrator description

The proposed demonstrator will include three hardware packages AURIX 3G + PPU (silicon, package, testing), EVAL board for intrinsic AI applications and the 3D Application Board architecture, where a complete V-model-process-chain is used for the development of an affordable 3D perception system.

AI oriented algorithms will be developed and implemented to enable the optical 360-degree object recognition based on the 2D video and the distance information (3rd dimension) from the ToF measurement. In addition, the next AURIX microcontroller generation will be enhanced with a PPU (Parallel Processing Unit) to perform complex vector and matrix calculations. Some of the required AI control functions will be designated to be implemented on IFAG's safety-oriented AURIX® 3G platform to reduce system cost and power consumption.

It is planned to develop a methodology (toolchain) to optimize the link between HW/SW application integration and the related development process. This includes the development and verification of AI-based algorithms using model-based development, high-level tools like TensorFlow, ONNX and Matlab/Simulink.

Since accurate distance measuring is crucial for the application, it is planned to work on intelligent calibration (e.g. continuous calibration even during operation to enable distance measurements with high absolute accuracy), modulation coding (e.g. to mitigate interference from multipath reflections created by the cover glass, highly reflective surfaces or particles such as rain, snow, etc.), and sensor authentication (e.g. to ensure that the data are not being manipulated and to prove that the data have originated from the claimed sensor).

The whole setup will be supplemented by a power management integrated circuit (PMIC) capable of withstanding the micro controller power demand and voltage accuracy. The PMIC will integrate Functional Safety compliance to ensure the system could achieve proper ASIL level in respect to ISO 26262. Embedded intelligence will be explored for the novel PMIC design to enhance fault recognition and improve both functional safety and system availability.

The technological demonstration of jointly defined use cases (WP1) will be done within a lab setup. Based on results, further possible integrations and functional validations will be discussed in collaboration with the Supply Chain 1, 2, 3, and 4 teams.

The main computation tasks of the demonstrator include the calibration of the multi-sensor system, stitching of 3D and 2D sensor data and object recognition in the field-of-view of the perception system.

4.5.2 Objectives

The main functional objectives of the SC6.5 demonstrator can be summarized as follows:

1. Prototype and validate the developed concepts.
2. Develop the architecture at the component level to address high-performance, energy-efficient AI computing.
3. Make use of sensors and systems for cost-efficient and instantaneous scene interpretation.
 - a. Surround view generation based on 3D ToF sensor array
 - b. Surrounding object recognition based on 2D and 3D data from ToF sensors
 - c. Automatic calibration of sensors

The demonstrator will initially serve as a proof-of-concept for AI-enhanced 360° vision capabilities while taking into account broader objectives, like cost-efficiency for automotive applications.

4.5.3 Alignment to the project and SC6 objectives

The following project objectives are addressed in SCD 6.5:

- Level 0 (EU/ECSEL): ECAS 2030: Mobility Trends (Electrification, Standardization, **Automation, Digitalization**)
- Level 1: AI4CSM project: **O1 (mobile platform), O2 (embedded intelligence), O3 (AI accelerator chip), O4 (trustable AI), O5 (functional systems)**
- Level 2: Objectives of AI4CSM Supply Chains: technologies developed within SC6 =>
 - Availability of low-power high-cognition sensors and systems for computationally cheap (cost-efficient) and instantaneous scene interpretation
 - Availability of next generation cognitive sensor hardware and embedded software solutions enabling enhanced and instantaneous scene interpretation while minimizing its local power consumption and optimizing its computational resources/approach.
 - Safe traffic/vehicle (SC1, 2, 3,4)
- Level 3: Availability of Chips (μ C, AI/PPU, ToF Sensor), Application Boards, System Design Methodology, Tool Chain, Algorithm

4.5.4 Partners and their role

The partners involved in the demonstrator and their roles are the following:

- **EDI**: sub system coordination:
 - perception system requirements and architecture
 - subsystem assembly: 3D ToF array, AURIX®, PMIC

- perception algorithms
- **IFAG**: AURIX® platform / tool chain
- **IFAT**: ToF sensor chip, calibration
- **IFI**: power management integrated circuit (PMIC)
- **IFIN**: sensor fusion AI algorithms
- **SSol**: custom graphical interface for visualization

4.5.5 Demonstrator architecture

Figure 29 and Figure 30 depict the preliminary architecture variants of the demonstrator. The left variant assumes registration and stitching first and AI processing second. The right variant has a changed order in the pipeline with semantic processing first and registration followed by an output merge afterwards.

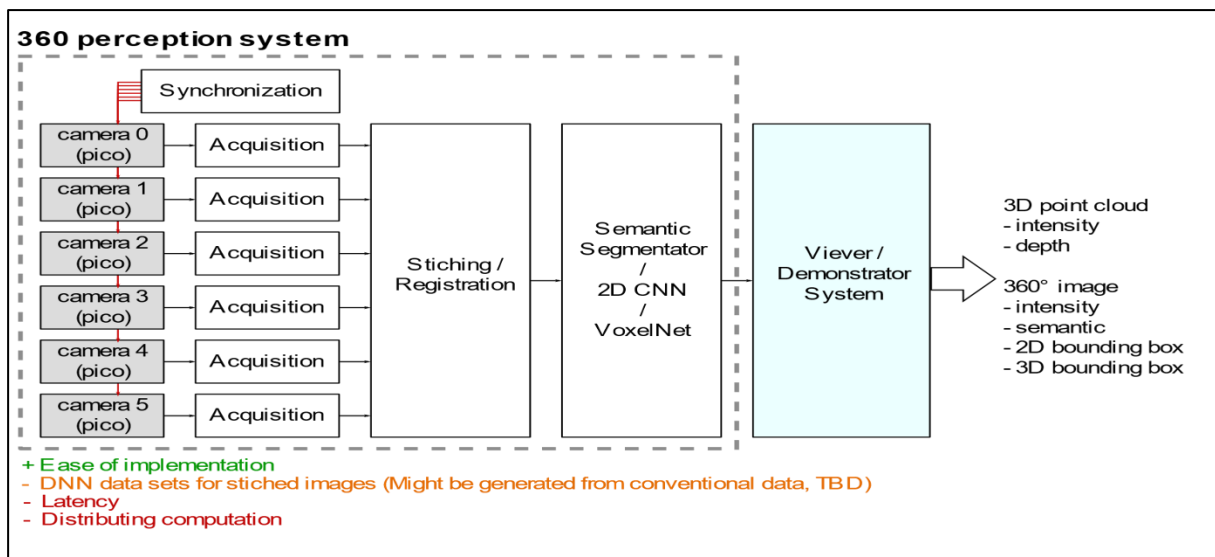


FIGURE 29: SCD 6.5 ARCHITECTURE VARIANT #1

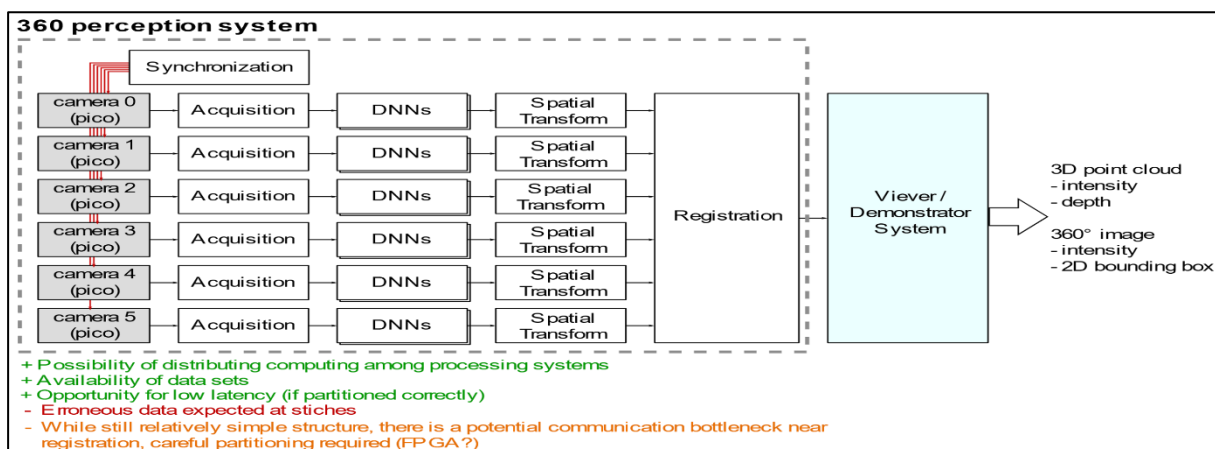


FIGURE 30: SCD 6.5 ARCHITECTURE VARIANT #2

The first architecture variant has a relatively simple structure, but it has some drawbacks, including a relative lack of possibilities for distribution computations, which may lead to higher latencies. It also

assumes the object recognition algorithms to run on a fully stitched image, which could lead to additional complexity for processing the combined image.

The second variant enables more parallel processing and simplifies object recognition by keeping the input data separate, but it also introduces additional efforts in combining sensor data along with semantic data to form the complete output.

These observations will be evaluated during the implementation of Task 2.6 “System level design for AI-enabled perception and sensors fusion systems” to produce the final architecture variant, reported in D2.7 “Report on system level architectures and designs for AI-enabled perception and sensors fusion systems”.

4.5.6 Requirements

TABLE 28: #1 FR SCD 6.5

| | #1 Functional Requirements / FR |
|--------------------------------------|--|
| ID | AI4CSM_WP1_SDC6.5_1 |
| FR Naming | Perception system - surround view |
| Description of FR | The perception system shall combine the data from all ToF-sensors into a seamless 360-degree view. |
| What is measured: | Position/orientation deviation of a single camera. |
| KPI | [mm] deviation |
| Method of collection and measurement | Use a test stand and/or online verification datasets. |
| Target Value | Demonstrated 360-degree view |
| Verification and validation method | Compare measured results to a ground truth. |

TABLE 29: #2 FR SCD 6.5

| | #2 Functional Requirements / FR |
|--------------------------------------|--|
| ID | AI4CSM_WP1_SDC6.5_4 |
| FR Naming | Perception system - object recognition |
| Description of FR | The perception system shall be capable of recognizing at least the following objects: humans, vehicles (2-wheel, 4-wheel). |
| What is measured: | System classes. |
| KPI | [%] Mean average precision. |
| Method of collection and measurement | Online datasets and data from cameras. |
| Target Value | 40% mAP |
| Verification and validation method | Apply used model on an online dataset, compare with ground truth. |

TABLE 30: #3 FR SCD 6.5

| | #3 Functional Requirements / FR |
|--------------------------------------|---|
| ID | AI4CSM_WP1_SDC6.5_10 |
| FR Naming | Visualization - show point cloud |
| Description of FR | The visualization system shall visualize a stream of point clouds spanning a 360-degree field of view, mapping infrared values to each point. |
| What is measured: | How easy it is to perceive the visual information by a human (i.e., the driver/user of a vehicle). |
| KPI | A human (i.e., the driver/user of a vehicle) can recognize the visualized objects |
| Method of collection and measurement | Not relevant |
| Target Value | >95% |
| Verification and validation method | Tests with at least 20 humans |

TABLE 31: #1 NFR SCD 6.5

| | #1 Non-Functional Requirements / NFR |
|--------------------------------------|---|
| ID | AI4CSM_WP1_SDC6.5_2 |
| NFR Naming | Perception system - lighting invariance |
| Description of NFR | The perception system shall produce similar outputs in varying lighting conditions. |
| What is measured: | Transformation accuracy and object recognition accuracy |
| KPI | [%] deviation from results in standard lighting |
| Method of collection and measurement | Test stand with light sensor |
| Target Value | <20% deviation |
| Verification and validation method | Compare existing metrics on a relative scale while varying lighting conditions. |

TABLE 32: #2 NFR SCD 6.5

| | #2 Non-Functional Requirements / NFR |
|--------------------------------------|---|
| ID | AI4CSM_WP1_SDC6.5_5 |
| NFR Naming | Perception system - output data rate |
| Description of NFR | The perception system shall provide an output stream with a framerate of at least 10 FPS. |
| What is measured: | Output framerate of the perception system |
| KPI | [Hz] Framerate |
| Method of collection and measurement | Measure and compare timestamps. |
| Target Value | 10 Hz |

| | |
|------------------------------------|---------------------------------|
| Verification and validation method | Measure and compare timestamps. |
|------------------------------------|---------------------------------|

TABLE 33: #3 NFR SCD 6.5

| | #3 Non-Functional Requirements / NFR |
|--------------------------------------|---|
| ID | AI4CSM_WP1_SDC6.5_3 |
| NFR Naming | Perception system - capture synchronization |
| Description of NFR | The perception system shall synchronize captured images from all cameras with a deviation of no more than 1 ms. |
| What is measured: | Capture synchronization deviation |
| KPI | [ms] synchronization deviation |
| Method of collection and measurement | Let all sensors observe high precision timing gear. |
| Target Value | 1 ms |
| Verification and validation method | Compare captured times to target value. |

4.5.7 Validation, verification, and testing

The preliminary validation plan involves two verification media: test stands and online datasets. Test stands will be used for validating the performance of algorithms that need to fulfil different timing and coordinate transformation tasks. Online datasets will be used for algorithms that perform semantic operations (object recognition) and other algorithms that can benefit from virtual ground truths. Refer to the requirements for additional information.

The validation and verification process will take place in several steps, initially testing the performance of individual subsystems of the demonstrator, and ending with verification tests that consider the whole system in a near-final scenario.

5 Conclusion

5.1 Contribution to overall picture

Task 1.6 laid the groundwork for the rest of SC6. The following work packages can further deepen the work done and carry out their tasks on a sound basis. The five demonstrators have given a detailed insight into the planned works in the upcoming project years.

As discussed in meetings on a 3-week basis, a template was generated for the demonstrator leads and their partners to fill. The focus was on the technical requirements and specifications. Each of the partners had to provide an overview of the demonstrator in general and give a description. Relations to the objectives were drawn, and a first draft for the architecture was provided. The requirements were split into functional and non-functional. The goal here was to have 3 of each for every demonstrator to provide precise and meaningful indicators.

Based on the input, further deepening of the work can be managed by the next upcoming work packages, starting with work package 2.

5.2 Relation to the state-of-the-art and progress beyond it

| Partner/Topic | Description |
|---------------|--|
| NXP | <p>SCD6.1.C: While most of the state-of-the-art focuses mainly on optimising AI models accuracy, the work proposed in this project moves towards hardware-aware optimisation, automating the design of efficient AI models by taking the edge node properties into account during the optimisation process, resulting in improved performance and guaranteed compatibility at design time. See the references below for more information:</p> <ul style="list-style-type: none"> [1] Cai, et al. TEA-DNN: the quest for time-energy-accuracy co-optimised deep neural networks, 2019 [2] Federov, et al., Sparse: Sparse architecture search for cnns on resource-constrained microcontrollers, 2019 [3] Parsa, et al., Pabo: Pseudo agent-based multi-objective bayesian hyperparameter optimisation for efficient neural accelerator design, 2019 [4] Parsa, et al., Bayesian Multi-objective Hyperparameter Optimisation for Accurate, Fast, and Efficient Neural Network Accelerator Design, 2020 [5] Vidnerova, et al. Multiobjective Evolution for Convolutional Neural Network Architecture Search, 2020 [6] Yang, et al., Cars: Continuous evolution for efficient neural architecture search, 2020 [7] Schorn, et al., Automated design of error-resilient and hardware-efficient deep neural networks, 2020 [8] Tan, et al. Mnasnet: Platform-aware neural architecture search for mobile, 2019 [9] Gupta, et al., Accelerator-aware Neural Network Design using AutoML, 2020 [10] Cai, et al., Proxylessnas: Direct neural architecture search on target task and hardware, 2018 [11] Cai, et al., AutoML for Architecting Efficient and Specialized Neural Networks, 2020 [12] Green, et al., Rapdarts: Resource-aware progressive differentiable architecture search, 2020 [13] Stamoulis, et al., Single-Path NAS: Designing Hardware-Efficient ConvNets in Less Than 4 Hours, 2020 [14] Jin, et al., Auto-Keras: An Efficient Neural Architecture Search System, 2018 [15] Cai, et al., Once-for-All: Train One Network and Specialize it for Efficient Deployment, 2019 [16] Fang, et al., Fast Neural Network Adaptation via Parameter Remapping and Architecture Search, 2020 |

| | |
|------|---|
| | <p>[17] Fang, et al., FNA++: Fast Network Adaptation via Parameter Remapping and Architecture Search, 2020</p> <p>SCD6.1.B: State-of-the art focuses either on non-coherent combining of data from multiple radar sensors or on coherent combining with constraints on the configuration of transmitting and receiving antennas. In our approach, we don't constrain antenna configurations and want to exploit coherent processing of the multiple radar sensors.</p> <p>[18] Gottinger, M. et.al. Coherent Automotive Radar Networks: The Next Generation of Radar-Based Imaging and Mapping, IEEE Journal of Microwaves, Vol.1, Issue 1, p.149-163, January 2021</p> <p>[19] Gottinger, M. et.al. Coherent Full-Duplex Double-Sided Two-Way Ranging and Velocity Measurement Between Separate Incoherent Radio Units, IEEE Transactions on Microwave Theory and Techniques, Vol. 67, Issue 5, p.2045-2061, May 2019</p> <p>[20] Frischen, A. et.al. Coherent Measurements With MIMO Radar Networks of Incoherent FMCW Sensor Nodes, IEEE Microwave and Wireless Component Letters, Vol. 30, No. 7, July 2020</p> <p>[21] Ravish Suvana, A. et.al. Fusion of Data from Multiple Automotive Radars for High-Resolution DoA Estimation, IEEE Radar Conference 2022</p> |
| BUT | <p>The 3D surrounding maps are currently storing the original aligned data, which is cumbersome and hard to share due to the large memory footprint. Small vectorised 3D maps saving only the extracted objects from the original data will be easy to share, browse and process.</p> <p>Current autonomous vehicles rely on their own sensors only. Sharing of the map among the vehicles brings new angle of view which is unreachable by vehicle's own sensors, which improves robustness of perception system and improves safety of a vehicle operation. When the map is shared, it is also possible to estimate sensor failures and thus reaching even more safe operations.</p> |
| EDI | <p>The main role of different sensors¹ used in automotive is to make driving safer and easier. A lot of current research goes into Surround View Systems^{2,3} that can assist drivers to safely maneuver in different situations where human perception is limited. In such systems the chosen sensors are often RGB cameras (or infrared for night vision), which don't provide depth information. The AI-based near-field, high resolution 360-degree perception system, based on 3D ToF imaging sensors, will make it possible to not only get visual data but also semantically enhanced distance information of surroundings, thereby adding dynamic situational awareness to the vehicle.</p> |
| IFAG | <p>Next generation AURIX® will incorporate a new PPU to enable efficient implementation of AI algorithms</p> |
| IFAT | <p>Available ToF Sensors require off-chip processing to calculate distance values from measured RAW values. This process involves capturing multiple frames of RAW data, which are combined in a single distance frame. Each of the RAW frames requires individual calibration in order to reduce systematic errors. Next generations of sensors will offer operation modes where fewer RAW frames are required, and the calibration effort is lower to calculate a single depth frame. This reduces the load on the application controller in order to free resources for e.g. AI Algorithms.</p> |

¹Biyao Wang, Yi Han, Di Tian, Tian Guan, "Sensor-Based Environmental Perception Technology for Intelligent Vehicles", Journal of Sensors, vol. 2021, Article ID 8199361, 14 pages, 2021. <https://doi.org/10.1155/2021/8199361>

²Al-Hami, M., Casas, R., El Salhi, S., Awwad, S., & Hussein, F. (2021). Real-Time Bird's Eye Surround View System: An Embedded Perspective. Applied Artificial Intelligence, 35(10), 765–781. doi:10.1080/08839514.2021.1935587

³<https://www.nxp.com/applications/automotive/adas-and-highly-automated-driving/surround-view-:SURROUND-VIEW-PARK-ASSIST-SYSTEM>

| | |
|-----------|--|
| IFI | Power Management IC is currently supporting functional safety micro controller devices in the automotive environment having a current demand up to approximately 2A for core logic. The need for more computational logic is nevertheless showing a tremendous boost of power consumption that will bring the next generation micro controller already in the range of 7A (or more) current. Moreover, the advancement in technology scaling is moving the voltage set from current 1.25V to 0.9V-1V with consequent increase of needed precision (absolute value) for the regulated voltage, that combined with larger load step dynamic response, will further challenge the DCDC architecture and regulatory scheme. |
| IFIN | Testing Sensor Fusion AI Algorithms along with support from IFAG and run in AURIX |
| IMA | <p>ToFs are usually an integrated array of purpose-designed photodiodes that detects the radiation reflected by an object. From the digital data provided by the sensor device, the distance information can be derived by dedicated software algorithm. Optionally, supports laser- and LED-illumination. High sensitive ToF cameras usually use arrays 8x8 zones resolution, 32x32 pixels.</p> <p>The STM ToF tested in the demonstrator possesses ranging flow up to 4000 mm, at fast speed (60HZ), 4x4 (16 zone) and 8x8 (64 zone) resolutions. 2 operation modes - Continuous & Autonomous</p> <p>Integration time:</p> <ul style="list-style-type: none"> • only available using Autonomous ranging mode. • It allows the user to change the time. • Has no effect with continuous mode. <p>The effect of integration time is different for 4x4 and 8x8 resolutions</p> |
| IMEC | State-of-the-art focuses on conventional neural network architectures for classification road users like cars and pedestrians this work focuses on spiking neural network architecture in combination with an event-based neuromorphic sensor fusion. In this way, such an architecture will provide a robust, fail-tolerant, power-efficient and low-latency inference. |
| INNAT | State-of-the-art approaches rely on complex neural network topologies for the detection of time-series patterns. This demonstrator leverages the temporal capabilities of spiking neural networks and the power-efficiency of analogue-mixed signal implementations to realise always-on time-series processing capabilities for resource constrained edge applications. |
| NXPDE | While conventional tuning tools only focus on a small set of parameters optimised by humans for specific conditions and switching between them during runtime, our method aims to automatise data generation process. By creating a big database, we can tune a neural network to tune ISP in a vast scenario and achieve better ISP tuning performance. |
| NXTECH | SCD 6.3: AI-enabled HW/SW modules for small size ECAS vehicles, including compact design and scalable solutions for an AI based V2X perception platform, combining different sensors and integration with cognitive computing and secure communication for exchange with edge computing infrastructure. |
| PAXTER | SCD 6.3: Solutions for the increased demand for last mile delivery and at the same time reduce environmental impact, including innovative transportation infrastructure and new commercial delivery models based on fleet of electric vehicles. |
| SINTEF | SCD 6.3: Novel concept and architecture for sensors and data fusion to improve the processing of several sources of data from perception sensors, beyond the individual information received from each of the data sources. |
| TGLV/SSOL | There is a clear demand for graphic user interfaces between humans inside and outside of transport systems and AI-enabled technical perception systems, which have to be: easy to understand, intuitive, easily adaptable, safe, secure, unobtrusive and reliable. Among others, object visualisation and easy/intuitive perception are crucial factors for graphic user interfaces related to car-sharing mobility services. |

| | |
|---------|--|
| TUDELFT | Spiking neural network models are compact when compared to conventional neural network architectures. In this demonstrator, this advantage of SNNs is leveraged to deliver high-performance intelligence into a heavily resource-constrained edge application. |
|---------|--|

5.3 Impacts to other WPs, Tasks and SCs

As the Task 1.6. focusses on the system and subsystem level designs based on the technical requirements and specifications developed in WP1. The designs descriptions include different types of perception sensors, sensor fusion techniques and HW/SW AI-based platforms. The findings will be directly used within the further elaboration of the SC6 and also other Work Packages, Tasks of further Supply chains, as shown in the following list:

| Partner/Topic | Description |
|---------------|---|
| NXP | Task 2.5 [SC5]: System level design for Connectivity and Communications: NXP will perform modelling and feasibility studies of the cross protocol, in-car communication architecture as specified in WP1, applying network traffic engineering technologies and investigating the specified low latency, safety and Ethernet security requirements. |
| BUT | The abovementioned requirements for Demonstrator SCD6.4 will be taken into account during system level design within T2.6 of WP2. |
| EDI | EDI will exploit the defined requirements from this deliverable to define system architecture in WP2, Task 2.6 “System level design for AI-enabled perception and sensors fusion system”, as well as will for the guidance of all the technical developments in WP3 and WP4, Task 3.4 “Components design for or AI-enabled perception and sensors fusion” and Task 4.5 “Embedded HW/SW and computing algorithms for perception and sensors fusion systems and platforms” and integration tasks in WP5, Task 5.2 “Integration of the AI based EV demo vehicle” and Task 5.6 “Integration of AI-based perception systems and platforms”. Last but not least, these requirements will be used to validate the developed system in WP6, Task 6.6 “Validation, verification and testing of AI-based perception systems and platform for ECAS vehicles”. In addition, the results will be exploited directly in SC2 “EV 2030 by AI inside”. |
| IFAG | The requirements collected for SCD6.5 application will influence the specifications of upcoming AURIX® generations – the full development V-cycle (WP1 to WP6) will be influenced by WP1 results. IFAG will also collect requirements related to SC1, SC2, SC3, SC4 and SC6 and incorporate all those results into AURIX® product roadmap |
| IFAT | The collected requirements will influence the product definition for all future generations of ToF Sensors. Specifically WP2/Task 2.6 will take the requirements as input. |
| IFI | The functional safety PMIC device developed to support the micro controller used in SC6 is going to be also exploited in SC3 and SC4 to support different demonstrators. The activities in task 1.6 are therefore synergic to the overall WP1 activities of IFI in the three SCs and represent the prerequisite for all following WPs (WP2, WP3, WP5 and WP6). The power management architecture definition will indeed benefit of this requirements identification and the PMIC device design. The identified requirements will also drive the subsequent validation of the PMIC in dedicated laboratory environment and in the integration in the demonstrator board. |
| IFIN | Depending on the requirements, different AI Sensor fusion algorithms have to be understood. |
| IMA | N/A |
| IMEC | Outcome of this deliverable will be used in WP2 (Task 2.6) for the system level architectures and designs for AI-enabled perception and sensors fusion systems. AI-accelerator |

| | |
|-----------|---|
| | requirements and specification will be used in WP3 (Task 3.4) at prototyping the component and software requirements are fed into WP4 (Task 4.5) for developing computing algorithms and sensors fusion processing. |
| INNAT | The outcome of this deliverable defines the system-level architecture definition in WP2, hardware realisation in WP3, and the development of the spiking neural network algorithm in WP4. |
| NXPDE | Task 2.5 [SC5]: System level design for Connectivity and Communications: NXPDE will in detail study and design the security means of the cross protocol, in-car communication architecture specified in WP1, based on the outcome of the security use cases as identified and defined in WP1. Special attention will be paid to the security of the CAN (sub)systems. |
| NXTECH | SCD 6.3: The outcome will contribute to WP2 - System level design (in particular T2.6 - System level design for AI-enabled perception and sensors fusion systems), WP5 - System integration (in particular T5.6 - Integration of AI-based perception systems and platforms), and WP6 - Validation and tests (in particular T6.6 - Validation, verification and testing of AI-based perception systems and platform for ECAS vehicles). |
| PAXTER | SCD 6.3: The outcome will contribute to WP2 - System level design (in particular T2.6 - System level design for AI-enabled perception and sensors fusion systems), WP5 - System integration (in particular T5.6 - Integration of AI-based perception systems and platforms), and WP6 - Validation and tests (in particular T6.6 - Validation, verification and testing of AI-based perception systems and platform for ECAS vehicles). |
| SINTEF | SCD 6.3: The outcome will contribute to WP2 - System level design (in particular T2.6 - System level design for AI-enabled perception and sensors fusion systems), WP5 - System integration (in particular T5.6 - Integration of AI-based perception systems and platforms), WP6 - Validation and tests (in particular T6.6 - Validation, verification and testing of AI-based perception systems and platform for ECAS vehicles), and standardisation in WP7 (in particular T7.5 - Standardisation, certification and Ethical aspects). |
| TGLV/SSOL | The collected requirements and specifications will influence the development and integration of the graphic user interface. Specifically WP2/Task 2.6 will take the requirements as input. |
| TUDELFT | The outcome of this deliverable drives the SNN model development in WP4, as well as the general implementation of the model atop the system-level architecture in WP2. |

5.4 Contribution to demonstration

| Partner/Topic | Description |
|---------------|---|
| NXPEN | Demonstrate quantitative results of the multi-objective optimisation in addition to a qualitative demonstration through in-vehicle integration. |
| BUT | BUT designed the demonstrator SCD6.4 structure and researched the requirements bases. BUT will further work on bitrate reduction and vectorised 3D map maintaining and sharing, both are part of Demonstrator SCD6.4. |
| EDI | Research, development and integration of custom HW and AI algorithms in AI based near field, high resolution 360-degree perception system demonstrator. |
| IFAG | AURIX® and Infineon Radar application expertise as well as the provision of dedicated Evaluation boards will be the main contribution. In addition, there is the development of an AI related toolchain to be mentioned |
| IFAT | N/A |

| | |
|-----------|---|
| IFI | IFI will define the requirements for the PMIC device supporting the microcontroller in the evaluation board and will support the definition of additional power architecture constraints. |
| IFIN | N/A |
| IMA | The object detection system involved in the Demonstrator 6.4. |
| IMEC | The work demonstrates quantitative results of the multi-target VRU classification in addition to qualitative outcome of possibility of expanding NN accelerator for future system and application modifications. |
| INNAT | INNAT contributes to D6.2B with the system-level architecture for the accelerator platform, customised silicon, as well as the requisite algorithms and software mapped atop the platform in the context of the time-series pattern recognition use-case. |
| NXPDE | Developing algorithms and SW stack for data generation and training a deep learning model for auto tuning ISP. |
| NXTECH | SCD 6.3: Defining the technical requirements and specifications of the electronics and components for the communication, perception sensors and sensor fusion techniques to be integrated into the vehicles; and identifying the design trade-off for the integration of the electronics, communication, and components for perception modules. |
| PAXTER | SCD 6.3: Defining the high-level requirements and specifications for the perception sensors, sensor fusion techniques and the HW/SW platform for the vehicle's application scenarios. Focus is on the definition of the requirements and specifications of local demonstrator for platooning and fleet management use case scenarios for delivery of goods into a controlled urban/sub-urban environment. |
| SINTEF | SCD 6.3: Define and develop the technical requirements and specifications for evaluating and implementing compact, energy efficient and cost-effective perception sensors, together with sensor fusion techniques and AI-based platforms integrated into the small-size electric and connected vehicles. The work also includes standardisation activities for reliable and safe autonomous driving, including perception and sensor fusion functions. |
| TGLV/SSOL | SSOL will define the requirements and specifications for the graphic user interface and will support the development and integration of custom GUI in the AI-based near field, high resolution 360-degree perception system demonstrator. |
| TUDELFT | TU Delft collaborates with INNAT in the development of the spiking neural network models that are executed atop the accelerator platform. |

5.5 Other conclusions and lessons learned

| Partner/Topic | Description |
|---------------|--|
| NXPEN | During the execution of the activities related to this deliverable, we have learned that for this project, it is more appropriate to further elaborate on some requirements as part of the technical specification in WP2. |
| BUT | The available methods for data fusion of already classified and extracted objects must be deeper studied and elaborated. |
| EDI | N/A |
| IFAG | For the use cases discussed, it is not only ToF (driven by IFAT) but also Radar to be taken into account to become a significant Infineon contribution to AI4CSM – shift of prioritization will be driven in WP2 activities. |
| IFAT | IFAT will get detailed application requirements for surround view ToF systems which will be considered in future products. |
| IFI | N/A |

| | |
|-----------|---|
| IFIN | N/A |
| IMA | <p>Topics to be elaborated:</p> <ul style="list-style-type: none"> - quality of data sets for the algorithm creation, predictor quality - application development w.r.t. specification of the protected zone - code optimisation for limited computation |
| IMEC | During the activities in this WP, we analysed and learned ways and types of measurements of NN accelerator power, which was described in its functional requirements. |
| INNAT | N/A |
| NXPDE | <p>Non-convex optimisation methods for creating a big data set mapping camera sensor signal to optimal ISP parameters.</p> <p>Perceptual image similarity for measuring Tuning tool performance.</p> <p>Autoencoders for implementing DeepTuner network.</p> |
| NXTECH | No other conclusions and lessons learned beyond what is already included in the deliverable. |
| PAXTER | No other conclusions and lessons learned beyond what is already included in the deliverable. |
| SINTEF | No other conclusions and lessons learned beyond what is already included in the deliverable. |
| TGLV/SSOL | SSOL will get detailed application requirements for custom GUIs in transport services related to car-sharing mobility, which will be considered in future products. |
| TUDELFT | N/A |

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