Programmable Systems for Intelligence in Automobiles (PRYSTINE): Technical Progress after Year 2

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***Abstract*— Autonomous driving has the potential to disruptively change the automotive industry as we know it today. For this, fail-operational behavior is essential in the sense, plan, and act stages of the automation chain in order to handle safety-critical situations by its own, which currently is not reached with state-of-the-art approaches.**

The European ECSEL research project PRYSTINE realizes Fail-operational Urban Surround perceptION (FUSION) based on robust Radar and LiDAR sensor fusion and control functions in order to enable safe automated driving in urban and rural environments. This paper showcases some of the key results (e.g., novel Radar sensors, innovative embedded control and E/E architectures, pioneering sensor fusion approaches, AI controlled vehicle demonstrators) achieved until year 2.

Keywords*— *FUSION, fail-operational, perception

I. INTRODUCTION

PRYSTINE (PRogrammable sYSTems for INtelligence in AutomobilEs) realizes Fail-operational Urban Surround perceptION (FUSION) by researching and developing a set of key technologies. On lowest abstraction layer, novel components are researched and developed, such as robust Radar and LiDAR sensors, ASIL-D safety controllers, and number-crunching hardware accelerators. Using these components, PRYSTINE realizes the next generation autonomous driving platforms providing both ASIL-D embedded control and high-performance processing power. Dependable embedded control and embedded intelligence is then achieved by co-integration of signal processing and AI approaches. These novel sensor fusion and decision making solutions build the foundation for PRYSTINE's vehicular demonstrators.

This work presents in detail the latest research achievements and is structured as follows:

- Section II presents groundbreaking achievements on component level, in particular in the field of Radar sensors and RF interference mitigation.
- Section III proposes a novel method that improves sensor performance evaluations and that supports sensor setup definitions as requested and required by car manufactures.
- Section IV introduces one of PRYSTINE's next-generation automotive processing platforms featuring ASIL-D.
- Section V shows the latest advancements in vehicular E/E architectures.
- Section VI discloses novel breakthroughs in the field of sensor fusion and decision making.
- Section VII and Section VIII showcase the integration of the aforementioned technology enablers into automated driving demonstrators, such as passenger cars, heavy duty trucks (semi- and full-sized trailers), and AI controlled co-pilots.

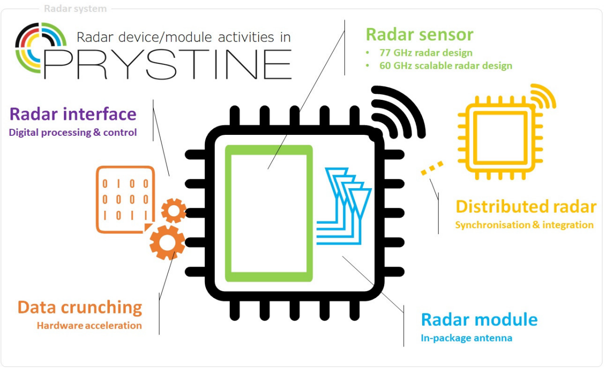

Fig. 1: Overview of PRYSTINE's Radar R&D activities.

II. NEXT GENERATION AUTOMOTIVE RADAR

PRYSTINE focusses on different vital parts and aspects of an entire radar system as illustrated in Fig. 1. One key aspect is the design of new Radar circuits offering improved sensing reliability and fail-operational features in order to address the FUSION goals. This includes the design of a radar sensor operating at 77 GHz and one at 60 GHz with fail-operational scalability features. Another key aspect is the packaging of mm-wave radar sensors, and more in particular the in-package integration of the antenna structures. Such integration is required for enabling compact and cost-efficient systems, but such implementation imposes severe design and performance challenges. PRYSTINE also focuses on realizing the interconnection between the high-performance radar chip and the rest of the system. This covers the digital processing, digital control, and the hardware accelerators. A final key aspect relates to the system integration of several radar sensors, and more in particular the synchronization between these sensors.

One of PRYSTINE's key Radar achievements is a low-power scalable 60-GHz FMCW Radar sensor in 28nm CMOS. Its sensitivity versus power scalability makes it a suitable building block for fail-operational systems. In case of battery malfunctioning, a fail-operational vehicle will dedicate its remaining battery power for driving the vehicle to a safe space. In such scenario, this Radar sensor enables to scale to a low-power mode and switch to button cell battery fueling. The reduced sensitivity will be acceptable as the vehicle will drive at reduced speed due to the failure operation. On the other hand, this Radar sensor can scale to a high sensitivity mode to take over the sensing functionality if other sensors on the vehicle fail. The scalability has been achieved by implementing aggressive duty cycling with a fast chip synthesizer, fast power up/down of all building blocks and sub-mW operation in down mode. The sensor is designed for increased sensing robustness and reliability by implementing a linear receiver and ultra-clean chirp signal with digital phase locked loop, which avoids ghost responses. Measurements on the fabricated chip (see Fig. 2) showed performances well beyond SotA with a 50mW consumption in continuous operation and a power-down scaling up to x100 [2]. This design was published and demonstrated at the prestigious ISSCC conference in 2020.

The quest for constantly increasing resolution in any domain of automotive Radar makes an accurate detection of extended targets more challenging, as reflections are spread across range, Doppler and angular dimensions. Furthermore, mutual radar interference in typical automotive scenarios imposes additional difficulties on

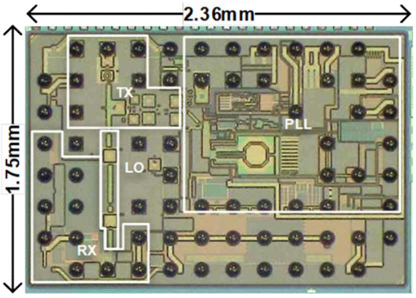

Fig. 2: Low-power scalable 60-GHz FMCW Radar sensor in 28nm CMOS by IMEC.

target detection by generally raising the noise floor and thus creating more false positive detections. Usually, state-of-the-art interference detection and mitigation algorithms are performed independently from the detection in a multi-stage process as depicted in Fig. 3 (a). In PRYSTINE, a deep learning based convolutional neural network architecture is utilized to create a combined interference mitigation and target detection in a single stage, as shown in Fig. 3 (b). This network is trained with a combination of real measurements and artificially introduced interference. Results show that it generalizes well over various noise effects induced by different interference modulation parameters, while increasing the detection probability for vulnerable road users like pedestrians or cyclist.

Based on the previous results regarding spectrogram based RFI mitigation, PRYSTINE's partners have developed a novel approach for RFI mitigation that employs fully convolutional neural networks (FCNs). The proposed architecture is fed with spectrograms of beat signals with noise and interference, and the output of the neural network is the range profile magnitude with mitigated interference. The general architecture of the network is shown in Fig. 4: the input spectrogram is processed through a series of conv blocks (composed of conv and pooling layers) until the vertical dimension is reduced to 1, while preserving the horizontal dimension (the number of FFT points). Fig. 5 depicts a comparison of the following approaches by using Radar data provided by NXP: FCN approach, original range profile with interference, reference range profile (no interference), RFI mitigation by zeroing the samples affected by interference.

III. PERFORMANCE ANALYSIS OF SENSOR SETUP CONCEPTS

In order to enable higher degrees of driving automation (referring to SAE level 3 to 5), vehicles will be equipped with more external sensors like cameras, Radars, LiDARs and ultrasonic sensors to perceive their surrounding environment sufficiently. It is a challenging task to define a sensor setup that covers all requirements. Regarding the development process of automated vehicles, the particular sensor setup has to be defined at a very early stage. The reason for this is that all subsequent data processing parts of the perception system like detection algorithms, data fusion, the environment model and Advanced Driver Assistance System (ADAS) functions are based on it. Furthermore, the sensor setup affects the entire E/E-architecture, especially the layout of electronic control units (ECUs) and the power supply.

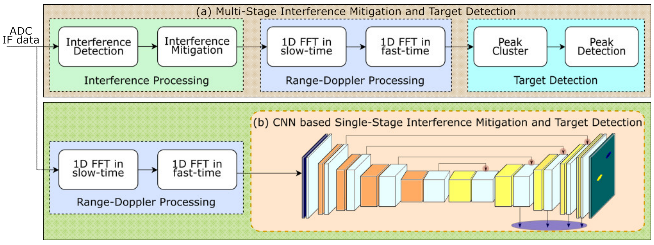

Fig. 3: CNN based one-stage interference mitigation and target detection framework (block diagram) developed by FAU University of Erlangen.

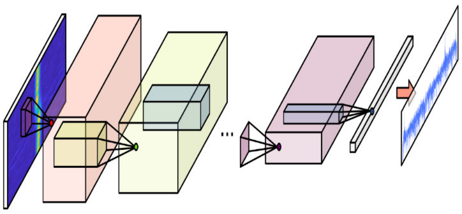

Fig. 4: General architecture of the FCN model developed by UPB for RFI mitigation.

It is not feasible to execute time-consuming and costly test drives to assess the overall performance of many different setup variations in this early concept phase to determine the best setup solution. Therefore, we established a suitable simulation framework and evaluation tool, which assists the procedure of evolving an optimal sensor setup for vehicle concepts [3].

Fig. 6 illustrates the simulation workflow of our evaluation tool as part (B) of the overall development process of perception systems (A)-(E), which is described in the following. First of all, the characteristics of individual sensors need to be identified (A). The sensor performance can be determined with datasheets, measurement protocols, and corner-case testing. In the next step (B), the established simulation tool is used to analyze the interaction of all sensors and thus to constitute the performance of the entire setup. The workflow starts with the generation of ground truth data. Here, IPG CarMaker is used to create relevant test scenarios. For the sensor simulation, the data fusion tool Baselabs Create is applied. In this part, the settings of probabilistic sensor models, e.g. field of view, range, accuracy and detection probability, are adjusted by using the information of step (A), and the virtual sensor setup is configured. During the simulation run, the ground truth data is modified according to these properties. Within the data fusion module, which relies on extended Kalman filters, the simulated sensor data of all individual sensors are fused with respect to the sensors' properties set in the sensor models. Afterwards, the fused sensor data and the ground truth data are compared with evaluation metrics to state the setup performance quantitatively. The evaluation suite includes the following metrics:

- Detection Rate and False Alarm Rate
- Position / Velocity / Acceleration Error
- Normalized Estimation Error Squared (NEES) to consider the confidence of the measurements
- Optimal Subpattern Assignment (OSPA) metric to measure the distribution difference
- Hausdorff metric to measure outliers

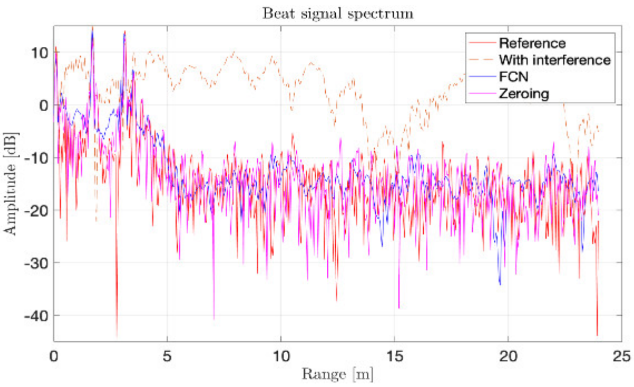

Fig. 5: RFI mitigation comparison.

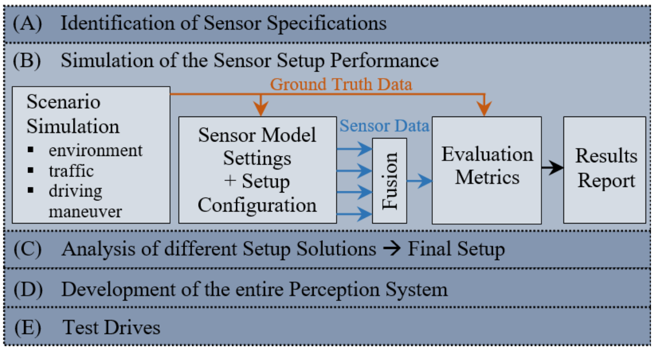

Fig. 6: Simulation workflow for the performance evaluation of different sensor setup concepts as part of the development procedure of automotive perception systems.

The results are summarized in a report. With this evaluation tool, different setup solutions are investigated regarding setup arrangement, sensor properties and mounting positions. The reports are used to apply cost-benefit analyses in order to select the final setup in step (C). Based on this decision, the subsequent perception system parts are developed (D). Finally, the overall system is optimized by considering the behavior of real sensors and environmental influences like weather and lighting conditions during test drives (E).

The established simulation-based evaluation method is an important instrument for automotive system engineers to analyze setup correlations and to define optimal setup solutions in a time- and cost-efficient way at this early development stage.

IV. HIGH PERFORMANCE EMBEDDED CONTROL AND INTELLIGENCE FOR FUSION

One key objective of PRYSTINE is to achieve a "dependable embedded control by co-integration of signal processing and AI approaches for FUSION on system level contributing to the development of next generation autonomous driving platforms and their components". Currently the consortium is working towards finalization of the respective implementations and is performing the integration activities for the specified demonstrators. For instance, a fail-over mechanism supporting functional safety as well as a fallback concept for environmental awareness and decision-making systems including security alerts are being finalized. To support demanding calculations, a fail-operational AI or CNN-based multiprocessor system (up to 256 cores) is being implemented. The partners are integrating, for instance, control functions and FUSION algorithm prototypes in their own passenger test vehicles and plan to present preliminary results of the AI-based algorithms soon. The technologies proposed will be further deployed in other demonstrators proving broader applicability (in heavy duty trucks and in a truck with trailer vehicles). In this paper we report on component management framework and novel data fusion and processing approaches developed by Institute of Electronics and Computer Science (EDI), which are integrated and tested on a real car - *EDI Drive by Wire (DbW)* car (Fig. 7), in an urban environment.

Fig. 7: EDI DbW car and its main components.

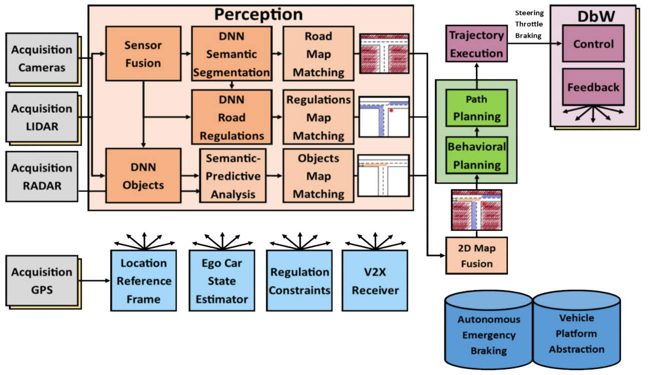

Fig. 8: Functional architecture of the EDI DbW car.

The functional architecture of the EDI DbW car shown in Fig. 8 can be broken down into the following high-level components: perception (sensors, data acquisition, data fusion, environment interpretation, perception fusion), path and behavioral planning (path planning, trajectory update, and execution, actuator signal generation) and global state estimation (ego car's state, traffic regulations, V2X interpretation, vehicle platform).

Sensors: to perceive the world and surrounding objects, several sensors (sensor systems) are used - twelve SEKONIX SF3323 Cameras, five Continental ARS-408 Radars, HDL-32 LiDAR, GPS RTK + IMU (for location reference frame, ego car state estimation and regulation constraints) and EDI V2X communication device (developed in H2020 ECSEL Autodrive project).

DNNs and Fusion: this part of the architecture is the main target and has different variations.

- Object detection and classification DNN is based on YOLOv3 [9]. This approach was chosen because of the SoA detection results coupled with the fast inference. Furthermore, when confronted with hardware limitations, the size of the YOLO model can be changed without retraining the model.

- Semantic Segmentation DNN processes the same camera frames as the object detector, but it attaches a class label to every pixel of the frame. This is crucial to determine where the vehicle is allowed to move as well as segments of road signs and markings to be cut out for smaller CNN-based classifiers. A MobileNet-based DeepLab model was chosen for this task [10]. The inference for the MobileNet-based DeepLab model was deployed, and initial results were gained on live data recorded from the city of Riga streets. The estimation for mIoU (mean Intersection over Union) on the test dataset was 74%, which is a relatively good result comparing to SoA [11]. Fig. 9 depicts preliminary results of MobileNet-based DeepLab.

Fig. 9: DeepLab inference on real data.

- Road Regulations DNN classifies paint markings and traffic regulation signs. This information is then combined with road segments to derive drivable regions in accordance with the traffic regulations. The used model is based on a variety of original LeNET CNN [12].
- Fusion of the perceived environment is achieved by combining all the outputs of the DNNs and sensors. This is accomplished by "overlaying" this information into a single 2D representation, which can be used for further trajectory estimation.

Embedded systems: besides sensors, *EDI DbW* car is equipped with *NVIDIA PX2* embedded system and *Aurix TC297* safety controller, handling the algorithms and ensures fail-aware, fail-safe and fail-operational functionality. If one of the high-performance platforms fails, the decision making module of the safety controller utilizes available vehicle state information to prioritize the feasible control signals.

Road, regulations and objects map matching: these components project previously determined information to the local 2D maps. 2D Map fusion component fuses these maps into one coherent image.

Behavioral planning and path planning: the behavioral planning component determines the behavior of the vehicle, e.g. where it would be necessary to stop or slow down according to traffic regulations, the path planning component uses this information to create a feasible trajectory.

Drive-by-wire system (DbW): EDI's DbW car is equipped with a DbW system to control steering, throttle and brake with a response rate of 100 times per second. It is based on the Open Source Car Control (OSCC) project, which is a reference design of DbW for Kia Soul EV vehicles. Implemented version of the DbW system was modified to meet the demonstrator needs. This includes addition of Single Board Computer (SBC) to the DbW unit which enables Ethernet connectivity of the DbW, besides the CAN bus. In such a way it is possible not only to send actuation commands by CAN bus, but also to deploy ROS service on SBC and to utilize the entire ROS ecosystem. The integration of the DbW unit is done with Nvidia Drive PX2 and the system was tested by running a Car-in-the-Loop (CIL) setup. CiL consists of Hardware-in-the-Loop (HiL) setup which uses Carla simulator for the sensor data acquisition and control signal sending back to the simulator processing data on the Nvidia Drive PX 2. The difference between CiL and HiL is that the entire car is used for control output signal validation which is generated by PID or MPC and terminates on the DbW system. This gives the possibility to test the entire data processing path from the sensor data acquisition step to the control of a real vehicle providing sustainable knowledge of the data processing latency.

In addition to all above mentioned, to better utilize system resources (e.g. data bandwidth, computational power) the implementation of **Variable Data Acquisition (VDA)** unit is proposed.

The inhouse software component management framework is used to facilitate the research and development process with modularity, reusability, and configurability of software components. Custom framework is preferred over conventional solutions like ROS, due to the increased overhead, which hinders the applicability in such real-time control systems as autonomous vehicles.

The proposed consists of two frameworks - ***compage*** and ***icom*** - their principal operation is illustrated in Fig. 10. *compage* enables a convenient way of managing and configuring software components, while ***icom*** (based on ZMQ) ensures essential communication paradigms (push-pull, publish-subscribe) and supports zero data copy, which is essential for saving bandwidth within a system.

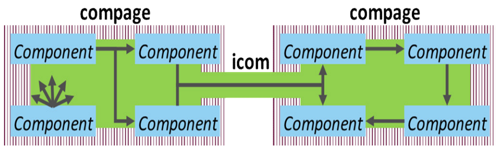

Fig. 10: Visual representation of software component management frameworks.

V. FAIL-OPERATIONAL E/E ARCHITECTURE ENABLING FUSION

Through increased acceptance of vehicle automation, there is an inherent market expectation for comprehensive, intelligent and adaptable control strategies. Such strategies enable a dependent automated takeover of vehicle controls from human drivers. The quality of the control is influenced by the sensed external environment and by vehicle's capability to respond to the gathered information in a style that is suitable for the vehicle occupants.

This process of environmental sensing, action planning and dependable control is facilitated by an electrical and electronic (E/E) architecture, supporting components and simulation activities that contribute to the development of control algorithm. Some of these supporting assets are developed in the PRYSTINE project. The initial prerequisite for the integration of the E/E architecture and relevant components is an overall fail-operational concept. A direct consequence is the usage of an integrative approach to all the components of the system i.e. optimized sensors, actuators, embedded safety controllers and communication modules. The development is showcased in three demonstrators. The demonstrators were restructured, so they partially depart from the original plan [1] and the previously reported activities [4].

The first demonstrator is a direct response to the increasing need for integration of centralized adaptive control automotive systems [5]. This integrative and technology agnostic platform aims to incorporate high-performance control units into the adaptable architecture. It is to enable efficient integration of various FUSION technologies with a strong focus on dependability, testing and validation [4].

The developed fail-operational E/E architecture (conceptualized in Fig. 11) is a basis for the integration of optimized vehicular E/E infrastructure and communication systems [5]. The semi-redundant components enable fail-operational monitoring, control and localized data collection. Upon identification of runtime failures, redundant components take over the control of the system and a decision is reached in terms of mode of operation (e.g. reduced operation to remain within safe operating boundaries) and communication of the warning messages to the vehicle occupants.

This demonstrator is strengthened by a simulation framework that supports the development of novel driving functionalities by enabling calibration, testing and validation before their release. Those activities are of particular importance for the improvement of human perception when developing ADAS/AD functionalities. The aim is to reduce real-life tests and accelerate the development process through the merger of the real and the virtual worlds (Fig. 12). The core of these activities focuses on interfacing diverse hardware and software components in a FUSION environment

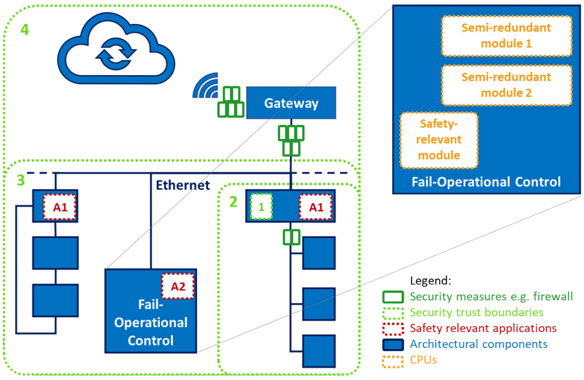

Fig. 11: Conceptual E/E architecture.

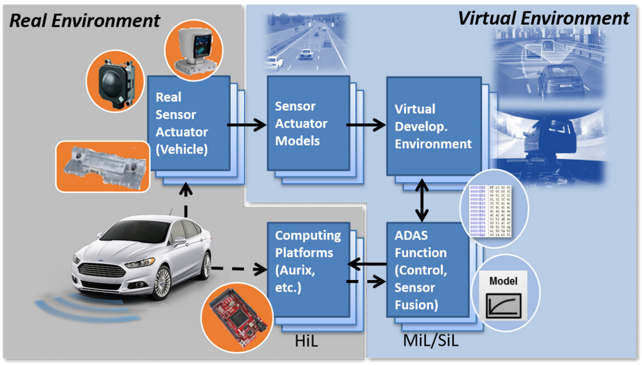

Fig. 12: ADAS/AD function development utilizing mixed reality.

aimed at their system integration.

Current activities in this demonstration include testing of individual hardware components and their suitability for integration into the fail-operational architecture, simulation of the on-road behavior needed for testing of the control algorithms, testing of the communication gateway together with data visualization and optimization of the beaconing technology. The future activities are directed towards the integration of individual components into a system.

The second demonstrator is looking into the usage of a simulation platform for the improvement of highly automated driving to ensure appropriate safety integrity. The demonstrator also investigates verification methodology, ensuring variability in terms of vehicle configurations and to account for a wide range of simulated (virtual drive) scenarios and failure modes. The simulation algorithms are ported to a modular embedded platform for real-drive testing. This modularity also enables integration of algorithms developed using a Semi-Markov approach [6] which contribute to a realistic representation of reality in the simulation environment. The resulting Dynamic Risk Assessment aids selection of a least risky trajectory. That empowers the autonomous vehicles to select appropriate navigation paths and to navigate encountered obstacles with an extremely high degree of confidence.

In its current state, the demonstrator shows the planned path for an autonomous vehicle using a Nominal Channel and the influence on that path by artificial fault injections in one of the Object Detection functions. The relevant safety procedures dictate an overruling of the Nominal Channel by the Safety Channel and the execution of a Minimal Risk Condition. A recovery procedure for the Nominal Channel and the resumption of the mission is also showcased. The channel interactions are depicted in Fig. 13, more details can be found in [7] and [8].

The future activities in this demonstration are also directed towards continuous integration and optimization of the simulation algorithms and safety analysis into the real-driving environment.

The third demonstrator is contributing to dynamically shaped reliable mobile communication for optimal network selection. It fulfils the objective of enabling optimal Vehicle to Network (V2N) communication for FUSION components and it improves Quality of Service (QoS) for V2N communication modules. Aside from ensuring QoS (including associated costs), the network selection also considers availability (coverage) and the possibility to use cellular V2N (C-V2N) services from the available networks. The QoS level of the V2N services may differ from one network to another. Hence there is a need to optimize the selection based on a geographical location. A global cloud-based database is implemented. It contains QoS parameters for all cellular networks, per geo-location. It will be populated by all vehicles that use this service (and may belong to a certain OEM, a cellular network, or a V2X operator). The database serves as a base for directing the vehicles to switch to a more suitable network, if available at its current location. The switch is performed in the vehicle's cellular modem, using standard (ETSI) AT commands, allowing an easy deployment to a standardized mobile infrastructure. The network switching may also be triggered by detection of QoS degradation beyond a critical level.

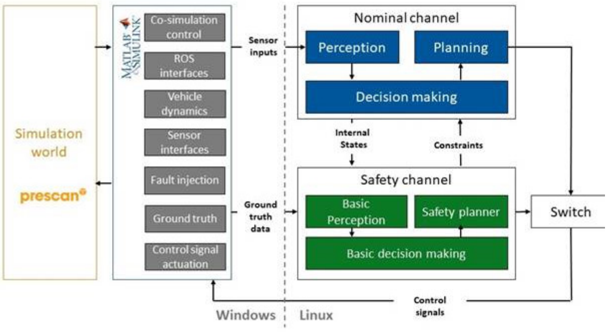

Fig. 13: Interactions between Nominal and Safety channels.

Current activities in this demonstration are based on the integration of the developed HW prototypes and QoS algorithms for prediction of improvements that are leveraging on the existing mobile network infrastructure. The complete integration of a system that is to deliver optimal vehicle communication via an optimal available network is to be performed in the PRYSTINE's remaining year.

VI. FUSION AND DECISION MAKING

Employing PRYSTINE's sensors, embedded intelligence, and E/E architecture, PRYSTNE heavily focuses on robust perception of the environment around the vehicle through the fusion of sensed data from a multitude of sensors (Radar, LiDAR, cameras…), thus realizing PRYSTINE's FUSION technology. The integration of data and knowledge from several sources is known as "data fusion". It is a process that deals with the association, correlation and combination of data and information from multiple sources to achieve refined positioning and identity estimates. It is mostly used for sensor fusion, since no sensor type works well for all tasks and under all environmental conditions. Sensor based systems generally suffer from several problems such as; "sensor deprivation", "limited spatial coverage", "limited temporal coverage", "imprecision" and "uncertainty". Imprecision and uncertainty are different concerns; "imprecision" occurs when measurements from individual sensors are limited to the precision of the employed sensing element, while "uncertainty" depends on the object being observed rather than the observing device, and occurs when features are missing (e.g., occlusions), when the sensor cannot measure all relevant attributes of the percept, or when the observation is ambiguous [1].

Towards overcoming these problems, it is perfectly possible to combine data from "multiple" and "diverse" sensors to produce rich, context aware data that eliminates the limitations in range or accuracy of the individual sensors. If data from more than one sensor and ideally more than one type of sensor can be combined in the right way, the combined data can be more accurate, more reliable or can simply provide a better understanding of the context in which the data is gathered. Therefore, sensor fusion is extremely important for autonomous functions to improve accuracy and reduce uncertainty. PRYSTINE's *vision* is to implement fusion and to achieve improved accuracy and more specific inferences than could be achieved by the use of a single sensor or data source alone.

Sensor fusion methods are widely used in many fields such as autonomous systems, remote sensing, video surveillance and military. PRYSTINE project concerns autonomous systems and sensor fusion is used in different applications such as perception, recognition, tracking, estimation and control. Applications addressed to "perception", "recognition" and "tracking" are used for development of the following systems.

Back Maneuver Assist System: this system aims to provide a solution for backing up a truck with a trailer, which is quite difficult

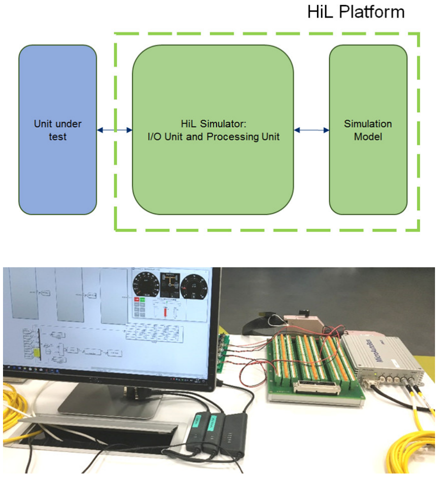

Fig. 14: Design of the HiL setup for back-maneuver assist system (top). Jetson TX2 platform running perception modules and Microautobox platform running "data fusion" and "path planning" modules in the HiL setup (bottom).

and prone to accidents. Most trailers are connected with a ball hitch which allows for a trailer to turn along with the tractor. However, the joint makes backing up a trailer a really difficult task, since the trailer can easily jut off at an angle. Additionally, it is difficult for the truck drivers to recognize obstacles due to the occlusive sizes of the vehicle. Backing up a heavy-duty trailer does not come naturally and requires much practice for truck drivers, which makes the need for a back maneuver and parking assist solution essential for articulated vehicles. Towards this end, a solution is developed (FORD, AVLTK, VIF), aiming to provide a robust solution with the employment of various sensors strengthened by the power of sensor fusion.

In the project's first year, the type, amount and location of the sensors were determined on the heavy duty vehicle (four LiDARs and six Radars to be mounted on the tractor and trailer, and a smart camera and a stereo camera to be mounted inside the cabin). Perception algorithms were developed and objects were detected from LiDAR and stereo camera sensors. Offline open source test data and simulated sensor data were utilized for validation of the first algorithms, In the second year, perception from remaining sensors are accomplished and individual LiDAR data is fused for better coverage and perception. Sensor Fusion algorithms are developed for fusing objects detected from the various sensors and subsequently for tracking these objects. Path planning algorithm is developed to extract the optimized paths for back maneuvering by the help of the dynamic map generated with using the tracked objects. These efforts are incrementally transferred to the project's "Heavy Duty Vehicle demonstration" after the accomplishment of successful HIL tests (Fig. 14).

Vulnerable Road User Detection: in the EU, 22% of road fatalities are pedestrians, while 8% are cyclists. Two core technologies of PRYSTINE's FUSION technologies are dedicated to protecting these groups. First one is focused on the Vulnerable Road User (VRU) detection based on Radars. In the last decade, Radar has substantially gained popularity in automotive, because moving to higher frequencies (towards mm-waves) enabled to drastically shrink the form factor of the Radar modules while increasing their sensing resolution. To increase the fail-operational environment perception robustness, multiple sensors are fused to exploit redundant information for ensuring reliable perception and to monitor the performance of each of the individual sensors. Simultaneous usage of Radar sensors comes, however, with increased interference risk. Therefore, such interference over different digitally modulated Radars was investigated in the project's first year and first round of data collection was accomplished based on field measurements. In the second year, a Radar based VRU detection and tracking system is implemented.

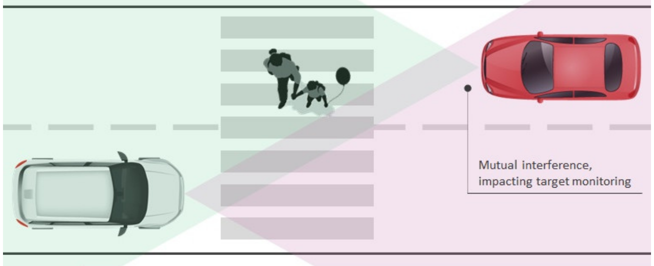

Fig. 15: Mutual interference of radars used in multi-sensor VRU detection.

Based on the studies, it was observed that, for FMCW, PMCW and OFDM, a tight radar synchronization achieves very concentrated interference in the range-Doppler domain, which can be filtered out by a combination of target tracking and Radar parameter hopping. At the other extreme, using completely different parameters create a noise-like interference that can be mitigated by the detection strategy (Fig. 15).

A second VRU detection and classification solution is based on multiple vision sensors and deep learning methods. A solution for detection and classification of VRUs using You Only Look Once (YOLO) and CenterNet algorithms is developed after observing different machine learning algorithms in terms of robustness and precision (Fig. 16). In the same way, a subset of four databases (Caltech, Daimler, KITTI, BDD100k) from all the datasets were selected in different scenarios. An architectural specification of a computer vision framework is developed to generalize the common computer vision tasks.

A third solution on VRU detection is based on a See-Through Sight (CiThruS) framework that not only addresses VRUs, but practically all possible vehicles and road users. CiThruS seeks to provide (i) blind area removal to spot weak road users before they enter the driver's natural field of view; (ii) automatic smartphone-based safety alerts which reduce road accidents and improve driver proactivity; and (iii) traffic analytics which improves driving experience by helping the driver to bypass traffic jams, roadworks, and other avoidable traffic events.

CiThruS' core functionality is being developed with the latest video technology. The driver's own vehicle will be made transparent by mounting multiple cameras around the vehicle and stitching the camera feeds together into a continuous 360-degree spherical video played back to the driver, e.g., on a windscreen. The vehicle will also receive camera feeds over X2V links from other vehicles and environmental obstructions. These external objects will also be made transparent by combining X2V feeds with the local video sphere through several video processing steps such as 3D feature map generation, vehicle localization, view synthesis, and masking after which the created see-through objects are virtually immersed on top of the video sphere (only edges seen).

For the time being, the development of the CiThruS video pipeline has primarily been carried out in an open-source simulation environment [13] which was designed to simulate different traffic scenes, vehicular camera settings, and holistic 360-degree traffic imaging in a virtual city. The environment is built with Unity 3D engine upon the open Windridge City Asset.

Fig. 16: VRU classification with deep learning networks.

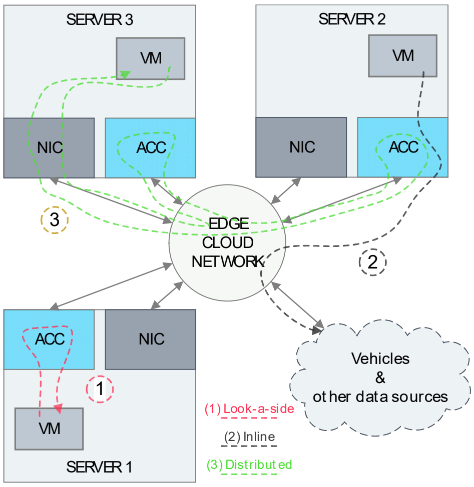

Fig. 17: CiThruS Edge Cloud architecture and acceleration schemes.

Furthermore, a designed proof-of-concept architecture of the CiThruS edge cloud computing platform will be implemented. The goals are to demonstrate how to achieve the performance requirements of the edge cloud, especially in terms of latency. The platform supports hardware acceleration such as FPGAs and GPUs which can be flexibly connected in order to better adapt to the processing tasks. Fig. 17 shows the CiThruS edge cloud architecture as well the acceleration scenarios it supports. Also, a management software for the cloud infrastructure is defined. The management software provides an easy and abstracted way for users to request and connect processing resources, such as Virtual Machines and accelerators. The platform's acceleration capabilities are leveraged by both safety alerts and CiThruS video pipeline for users to request and connect processing resources, such as Virtual Machines and accelerators.

Sensor fusion is also used for "control" applications. Sensor fusion capabilities combined with motion prediction enabled the improvement of AI-based and enhanced controllers. These controllers can decide and trigger the required trajectory actions in the specific situations.

Vehicle Control and Trajectory Planning: a trajectory planning and control algorithm is developed based on a Model Predictive Control (MPC) approach to work in different road scenarios. The algorithm allows accomplishment of (i) way-point tracking, (ii) lane center tracking, (iii) obstacle avoidance (for fixed and moving obstacles) and (iv) constraint satisfaction (e.g., road boundaries, speed limits). In the project's first year, the trajectory planning and control algorithm was designed and the MPC trajectory planning and control algorithm was tested in simulation using the Matlab/Simulink simulator. In the second year, vehicle dynamics are added to the simulations and realistic and complex road scenarios are considered in the tests including (i) collision avoidance with one or more, fixed or moving obstacles, (ii) lane changes, (iii) emergency stops, (iv) overtaking in different conditions. In these simulation tests, the MPC algorithm (in all its variants) showed a satisfactory capability of calculating optimal trajectories and provided effective control actions. These efforts of fusion based trajectory planning and vehicle control will be used in PRYSTINE's "Passenger Car" and "Shared Control" demonstrations.

As an additional contribution for "Passenger Car" and "Shared Control" demonstrations, a LiDAR Sensor Data Augmentation algorithm was achieved. This Sensor Data Augmentation algorithm not only provides high-quality and robust LiDAR data but also suppresses interferences caused from other LiDARs.

Suspension Control: this control solution is based on the fusion of multiple Radars and camera. In the first year, Radars were tested for road scanning and the best performance was achieved with fast repetition rate short-range scanning Radars. In the second year, low-profile road obstacles are detected using high frequency (77 GHz) Radars with appropriate algorithms. Virtual and software based sensors are added for allowing the derivation of road roughness and state. Additionally, the sensor fusion of virtual sensor enhanced data sets with directly obtained sensor data is being implemented for increased road safety and vehicle comfort Fig. 18.

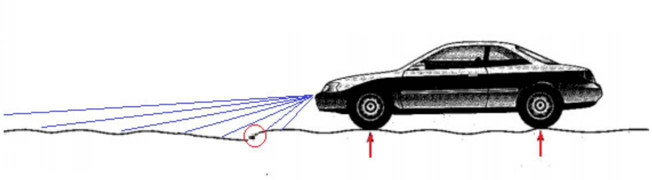

Fig. 18: Sensor fusion of Radars for detecting road geometry for vehicle suspension control.

Traffic Management: in the transition from AD levels 2, 3 to level 4, vehicles need to deal with more complex traffic conditions and road networks. Better understanding of traffic behavior supports the application of traffic measures more adequately, specifically in complex environments such as cities. These new capabilities enable the developments of Traffic Management as a Service. The proposed traffic management solution involves fusion of streaming traffic data from traffic controllers, floating car data (FCD) and automatic number-plate recognition (ANPR) cameras.

Sensors within the vehicle have a sense range of maximum 100-150 meters. Including predicted traffic states beyond the range of the on-board vehicle sensors offers a value adding service for in-vehicle decision making in order to achieve comfortable driving operations and to extent road safety. The traffic state prediction module involves fusing of real time data from various traffic sensors within a traffic modeling environment.

So far, the highway and urban traffic components are integrated. Furthermore, the combined parametric and nonparametric methods are improved by using traffic flow theory and continuous automated calibration of the parameters. Especially for the demand calibration, a better start solution for the demand matrices is estimated by incorporating a matrix calibration algorithm to fit demand patterns derived from the database with real time data of the traffic flow. Parking locations are specific origin-/destinations that can generate a lot of traffic at specific moments. Therefore, a machine learning application that generates real-time in-/outflow of parking locations is developed.

Based on the traffic state predictions, a service level for each road segment can be calculated. For this, a fuzzy function classification is made using density, flow and speed into a likelihood of being congested. Subsequently, these developments are tested in a modeling environment including real time data from traffic sensors for the city of Deventer (The Netherlands) and the highway A1 along Deventer.

Finally, an API for V2N communication with the ego-vehicle is implemented to provide the input (position and route of the vehicle) and report back the traffic information for the route downstream. These features will be used the project's "Shared Control demonstration".

VII. FUSION APPLICATION - HEAVY DUTY ELECTRIC VEHICLE

One of PRYSTINE's FUSION applications focuses on realizing a heavy duty vehicle demonstrator employing PRYSTINE's fail-operational autonomous driving functions and its data fusion from a wide range of sensors (Radar, LiDAR, camera, ultrasound, etc.). In the context of heavy duty vehicles, PRYSTINE aims to advance state-of-the-art by realizing an ambitious autonomous heavy-vehicle demonstrator for urban scenarios. Most autonomous developments today concentrate on long-haul highway related topics for heavy-vehicles. The need for high-precision maneuvers, combined with the size of heavy-vehicles, raises a high fatality risk, threatening the

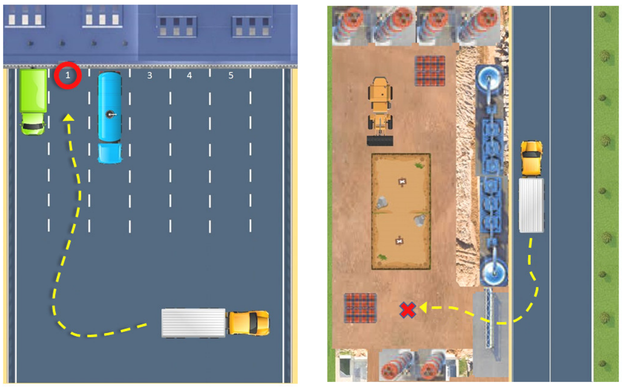

Fig. 19: Use case 1: back parking in a docking station (left) and Use Case 2: back entrance to a construction site (right).

accident-free mobility scenarios in urban environments. Towards annihilating these risks, the following demonstrations are pursued with corresponding use cases:

- A FORD heavy duty truck (semi-size trailer)
- A TTS heavy duty truck (full-size trailer)

FORD heavy duty truck: this demonstration will be performed in FORD Inönü Test Track with FORD F-Max truck. Specifically, two distinct use cases for trucks with trailers are considered to demonstrate the effective utilization of PRYSTINE's "Back Maneuver Assist System"; (i) parking in a Docking Station and (ii) backing in a Construction Site (see Fig. 19). For both use cases, it is common that the driver needs several trials to bring the trailer in the correct position, either to dock correctly to the dedicated slot in the docking station, or to bring the truck in position on the construction site. While the main concern during the docking station use case is the time spent to position the trailer, additional concerns at construction sites are the surrounding traffic and other road users, such as pedestrians. The solution shall be demonstrated with two use cases in FORD's Eskisehir Test Track.

In both of the use cases, the following sensors are integrated to the demo truck; 2×LiDARs, 6×Radars, 1×Stereo-Camera and 1×Smart-Camera. Secondly, perception, sensor fusion and path planning algorithms (developed in the scope of PRYSTINE, see Section VI) are integrated on the target platforms, NVidia Jetson TX2 and Dspace Microautobox that will also be eventually deployed to the demo truck together with an HMI device.

The third use case is the demonstration of a Facility Management System that aims to provide a proof of concept for the effective use of communication units developed in PRYSTINE. The system provides a solution for facility managers who are in charge of a Parking Station of a warehouse or a production plant, and who need to know and track the status of the parking gates together with the trucks in operation. The solution shall also be demonstrated in FORD's Eskisehir Test Track: Facility management in a parking station. In this use case (see Fig. 21), data about each parking slot of the facility is collected firstly, and environmental conditions of the facility are sensed by the sensors on the RSU. This data is transmitted by the RSU over a Bluetooth connection to the OBU deployed on the truck (connection A in Fig. 21). The data is subsequently conveyed to the truck's central processing unit. Meanwhile, vehicle specific data is collected and, slot and environment data are transmitted together with the vehicle data over internet (GSM based connection) to the Facility server using the Gateway Unit (connection B in Fig. 21). The Facility Server receives parking station's slot and environment data together with vehicle data from all trucks of the facility, and broadcasts this information over internet (connection C in Fig. 21). Any client platform, like a tablet, displays parking slots', environment's and truck's status to the Facility Manager simultaneously.

Fig. 20: Sensors mounted on the Ford heavy duty vehicle. A:Lidars, B: Radars, C:Smart-Camera, D:Stereo-Camera.

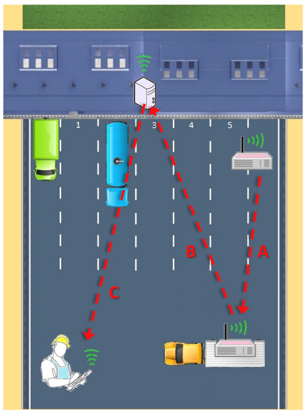

Fig. 21: Use Case 3: Facility management in a parking station.

Demo TTS heavy duty truck: this demonstration will be performed in the closed test area of TTS at Vihti in Finland and in the Training center at Nurmijärvi in Finland (urban type area with streets and crosses, partly closed) and during open road tests at multiple places in southern Finland.

Three use cases will be demonstrated to show the effective usage of autonomous developments towards traffic safety for long haul trucks: (i) right turn at urban area, (ii) lane change assistant for urban highway driving, (iii) start and stop safety at urban areas (see Fig. 23). For the demonstration of these three use cases PRYSTINE's sensor fusions solutions are integrated into the TTS truck. The fusion technology uses data from the following sensors: stereo cameras, 360˚ camera system and 24 GHz Radars (Fig. 24).

VIII. SHARED CONTROL AND ARBITRATION APPLICATIONS USING FUSION

In the PRYSTINE project, three demonstrators are developed with a special focus on a human-centered automated vehicle, where AD functionalities with different levels of driver's intervention are tested. These focus on the interaction between the automated system and the driver/occupant, pursuing safe decision-making and transitions leading to an intelligent co-driver able to assist the driver in manual and automated mode for various levels of automation.

Fig. 22: Open road tests (left) and TTS' closed test area, Vihti (right).

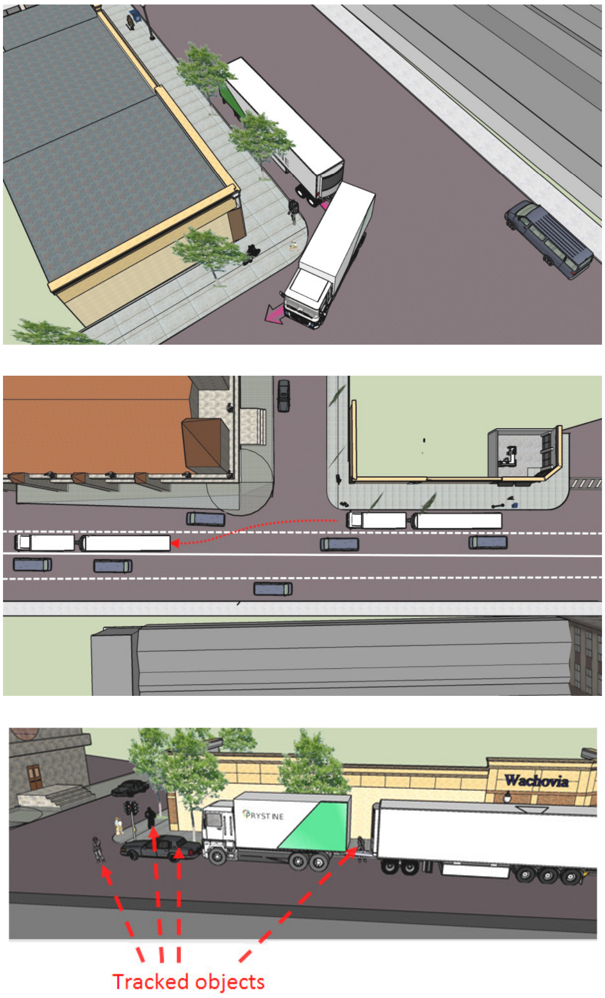

Fig. 23: TTS use case 1: right turn at urban area (top), Use case 2: lane change assistant (middle), Use case 3: start and stop safety (bottom).

Fig. 25 depicts the relationship between the three demonstrators, ranging from shared control (using a Driver in the Loop (DiL) and Hardware in the Loop (HiL) simulator), passing through traded and layered control (different levels of automation in the a passenger vehicle and an IRIZAR bus), and finally reaching to full automation with human-trained AI algorithms (using a passenger vehicle).

Shared control: is a simulator platform deploying a shared control scheme, based on an arbitration system considering a combination of information from scene conditions, automation status, maneuver risk, and driver status. It features fully automated operation, advanced support while on manual mode, and smooth authority transitions between the human driver and the automated system. It studies shared control in automated vehicles under the framework of fail-operational systems. The framework combines six automated driving modules that cooperate for the mutual understanding between driver and automated co-pilot. These subsystems are the core of the system design of this demonstrator:

Fig. 24: Sensors mounted on the TTS heavy duty vehicle. A: front camera, B: side Radars, C: electronic equipment (cabin).

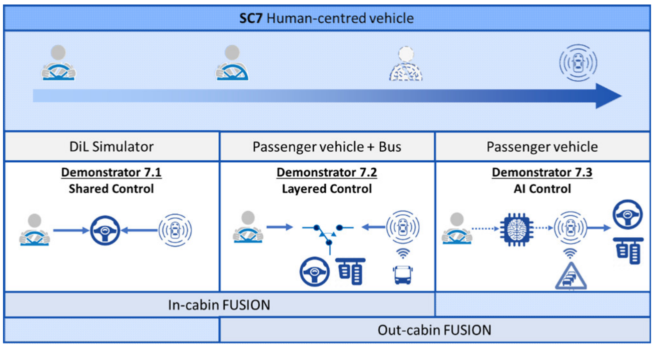

Fig. 25: Shared control and arbitration demonstrators

- *Fail-operational Perception:* provides information about the external environment conditions.
- *Driver Monitoring System (DMS):* monitors the state of the driver and need for assistance.
- *Arbitration:* assigns the authority to driver and automation at the tactical/maneuvering level.
- *Shared Controller:* supports the driver with feedback at the operational/control level.
- *Real-time Planning:* calculates the optimal collision-free trajectory in real-time.
- *Visual Human-Machine Interface (HMI):* shows automation perception, intention, and state.

The core of the functionalities is the development of a DiL ADAS that assists the driver according to his/her state, and considering different roles according to the level of automation. The main features are: drowsiness and distraction detection, a lane-keeping controller, an authority transition system, an HMI that shows to the driver real-time information related to the cooperation, and a collision assessment of the maneuver. All these functionalities will be integrated and tested in two AD simulators with DiL and HiL capabilities (see Fig. 26).

Layered Control: consists on a fully automated vehicle with a layered control system that fuses its own perception with infrastructure data and cooperative perception of an instrumented bus. It navigates a complex environment and automatically decides switching of automation levels considering ODD, maneuver complexity, and driver status.

The main objective this demonstrator is to design, develop and validate new functionalities for FUSION-based automated and connected vehicles where shared control is required. The

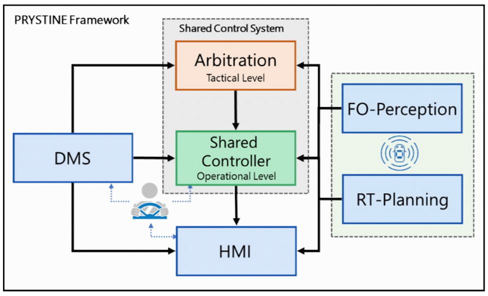

Fig. 26: Shared control demonstrator overall system design.

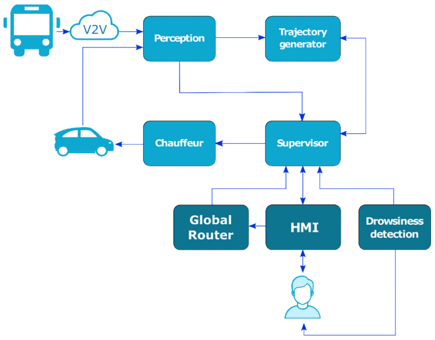

Fig. 27: General functional diagram of the Layer Control demonstrator.

demonstration in relevant scenarios will allow accelerating the deployment of more efficient and flexible systems in urban-like scenarios.

In this demonstrator, the automated vehicle will introduce a layered control architecture that is able to automatically switch from partial to high automation levels, namely SAE Level 2 (supervised city control); SAE Level 3 (city chauffeur); SAE Level 4 (Safe Stop), while monitoring the driving scenario specificities and sensors' health. The general functional scheme of this demonstrator is composed of different module as shown in Fig. 27.

AI Control: introduces artificial intelligence tactical level decision-making on a highly automated vehicle in highway and urban scenarios. On-board sensor data is fused together with a cloud-based traffic state and prediction service allowing the AI to make the tactical level decisions with a farther information horizon.

In this demonstrator, the architecture (Fig. 28) is built up by the various partners with developments coming mainly from PRYSTINE's the technology enablers. TU/e provides the car, takes care of the vision sensors (cameras) and the sensor fusion platform. NXP provides the radar sensors, Infineon provides the LiDAR sensors. DAT.mobility provides the traffic state ahead (e.g. the situation on the road 1 km ahead of the vehicle) and this traffic state is communicated to the car by ANYWI. TNO performs the prediction of the other road users which can then be used for decision making.

The knowledge graph database GRAKN representation is used to implement the desired entity-relationship scheme, thereby structuring any hierarchy found in traffic situations and managing the traffic rules applicable in that situation. This knowledge representation is then used for knowledge reasoning about rules (condition, conclusion), for example which tactical maneuvers are allowed in the given situation, and logical interference, for example, can the current traffic situation be considered as safe or could it end up in a collision when no further action is taken.

IX. CONCLUSION

The automation of vehicles has been identified as one major enabler to master the Grand Societal Challenges 'Individual Mobility' and 'Energy Efficiency'. Highly automated driving functions (ADF) are one major step to be taken. However, in order to achieve ADFs, fail-operational behavior is essential in the sense, plan, and act stages of the automation chain. PRYSTINE's target is to realize Fail-operational Urban Surround perceptION (FUSION), which is based on robust Radar and LiDAR sensor fusion, and control functions in order to enable safe automated driving in urban and rural environments. This work highlights the visions of PRYSTINE's research and development activities and showcases some groundbreaking results achieved until PRYSTINE's second year. During the upcoming final third year, PRYSTINE will preserve its spearhead position in ADF research and will thus be a key enabler who will usher in the ear of automated driving.

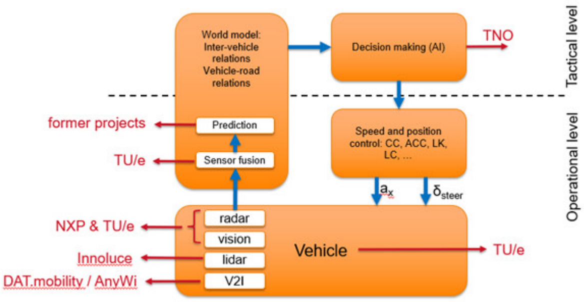

Fig. 28: AI control demonstrator's reference architecture.

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