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Robust perception systems for automated, connected, and electrified vehicles: advances from EU project ArchitectECA2030

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Abstract

The perception supply chain (SC1) of the ArchitectECA2030 project investigates failure modes, fault detection, and residual risk in perception systems of electrified, connected, and automated (ECA) vehicles. This accounts for the needs of a reliable understanding of the surrounding environment. The three demonstrators of SC1, described in this paper, address steps of a typical ECA usage cycle: charge - drive - restart charging. The foreign object detection (FOD) demonstrator improves safety within a wireless charging system. The robust physical sensors demonstrator creates a more robust perception by detecting failures within fused and single sensor data. The position enhancement demonstrator improves vehicle localization in areas with reduced GNSS signal coverage. All demonstrators are linked to the challenges that occur during the ECA vehicle usage cycle.

Keywords: Perception system. Validation, Electrified, connected and automated mobility;

1. Introduction

Future mobility will be composed of electrified, connected, and automated (ECA) vehicles. These different domains in technology must cooperate wisely to fulfill the legislative and end user requirements.

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Robust and safe solutions for future ECA mobility is the central goal of the European Union funded project ArchitectECA2030. In today's vehicles, it is still the human driver who decides on how to react to adverse environmental conditions. In automated vehicles, a combination of advanced driver assistant systems (ADAS), in conjunction with various sensors and computing units - the acquisition and perception system - controls the tasks of detecting objects in the immediate vicinity, such as other road users, and pedestrians, but also of deciding how to react to adverse weather conditions. To account all technical ECA domains, the project is structured in work packages and supply chains.

A supply chain, in the understanding of the project, is the collection of a number of demonstrators associated to a certain technology, e.g., perception or propulsion. Within the perception supply chain (SC1) as one out of five supply chains of the project, several demonstrators provide examples for perception systems for ECA vehicles aiming at more robust, trustable, and future-proof systems. These efforts in turn shall support the deployment of highly automated vehicles in the future. SC1 aims to identify possible failure modes of automated vehicles caused by its acquisition and perception system. It is also targeted to describe the propagation of faults and uncertainties caused by the perception system. Failures of the acquisition and perception system caused by internal errors as well as by uncertainties in the sensor- based measurements and the subsequent data processing may cause hazards and risks to people inside and outside the vehicle.

This paper shows which faults, failure modes, and failures are under investigation within different demonstrators. The demonstrators are connected via a typical usage cycle of an automated driving vehicle. The individual results of the various demonstrators including their specific key performance indicators (KPIs) will be discussed in dedicated individual journal publications in detail, currently in preparation or under review. This paper explains the approach of the SC1 of ArchitectECA2030 and provides insight on the demonstrators that are under development.

2. Approaches of the perception supply chain (SC1)

The present work shows how possible failure modes of automated vehicles caused by its acquisition and perception system are identified within the demonstrators of the supply chain. Demonstrators include radar (short- and long-range) and optical sensors (lidars, red, green, blue (RGB) cameras, thermal imagers, hyperspectral cameras) – at different time schedules during the day (day and night cycle) and under different environmental conditions (e.g., fog, rain, smoke, road conditions). SC1 approaches the overall project targets from the perspective of a typical ECA vehicle usage cycle. This usually has repeated and consecutive step as follows: charging process, route planning, driving from the start to the target location, parking manoeuvre, and charging again. Fig. 1 depicts an example of such a usage cycle of an ECA vehicle.

The demonstrators of the SC1, described in the subsequent sections, address challenging phases of the ECA vehicle usage cycle. The first demonstrator (described in section 3) in relation to the charging phase in the usage cycle, is about a foreign object detection solution as part of an automotive wireless charging system. This application aims to detect foreign objects within the wireless charging area to avoid hazards (e.g., fire and explosion) caused by high inductive voltages. Within the current Advanced Driver Assistance System (ADAS)/Autonomous Driving (AD) systems on the market, which are mostly systems with partial automation (SAE Level 2), the dynamic driving task is handled by the vehicle. However, most of the driving distance is still covered by the human driver. To extend existing operational design domains (ODDs), robust perception plays a crucial role as it provides input to the subsequent motion planning and control. The robust physical perception sensors demonstrator 4 aims to detect and identify faults in individual perception sensors (LiDAR and Radar) as well as within the fused sensor data enabling a more robust operation. The third demonstrator (section 5), also linked to the driving task in the usage cycle, aims to improve lateral localization of the vehicle with respect to the lane boundaries using machine learning algorithms in conjunction with a front looking camera.

Fig. 1. Challenging sections of an ECA vehicle usage cycle and the depiction of three demonstrators of the SC1.

3. Demonstrator 1: foreign object detection (FOD) within a wireless charging system

Demonstrator 1 of SC1 contributes to reliable, robust, and safe operation in the early stage of the usage cycle. The driving battery of electric vehicles can be charged by alternating current (AC) or direct current (DC). The DC power transfer requires an electrical connection (charging cable) between the vehicle and the charging station. AC power transfer can be realized wirelessly. This is particularly attractive, if the charging processes and/or the control of the vehicles are to be automated.

As it can be seen from the current versions of the European and American standards DIN CLC IEC/TS 61980-3 (2021) and SAE J2954 (2020), inductive power transfer is currently preferred by the standards organizations for wireless charging systems. Thereby, the ground assembly, which is located outside the vehicle, and the vehicle assembly form an ironless transformer. Its magnetic field also interacts with metallic objects that are not part of the charging system but are in the active area. Such metallic objects can be parts of the vehicle, but also undesired objects such as coins, metal foils, nails, etc. Due to eddy currents and hysteresis losses, metallic objects heat up in the magnetic field. According to SAE J2954 (2020), a heated metallic object is a potential safety hazard if it damages the surface on which it lies and, as a result, creates an electrical thermal issue, if it has a dangerous temperature to touch, if it becomes accessible, or if it ignites flammable materials with which it is in contact. The standard also specifies that such a hazard has to be avoided either by an appropriate design of the ground assembly coil or by using a metallic FOD system.

Many different methods have been proposed for the detection of metallic foreign objects. A good overview is given by Xia et al. (2020), Lu et al. (2022), Zhang et al. (2020), and Jeong et al. (2015). The decision for one of the methods is strongly influenced by the respective application. In the automotive sector, passive inductive sensors are currently favored because they are simple by design and do not require a separate signal source for control.

By the evaluation of the voltage induced in passive inductive sensors, one of the problems is to fade out the relatively strong magnetic field of the ground assembly coil and to reliably detect the comparatively weak magnetic fields of the metallic foreign objects. To solve this problem, as shown for example in Verghese et al. (2013), Rim and Mi (2017), and Thai et al. (2020), differential coils are often used to take advantage of the symmetry properties of the ground assembly coil. A disadvantage of this approach also arises directly from the principle of symmetry — if a sensor coil is symmetrically stimulated by a foreign object, then this is no longer detectable. However, experiments have shown that this effect can be almost completely compensated for foreign objects smaller than the ground assembly coil by a suitable design and arrangement of the sensor coils.

For each of the spatial components of the magnetic field, there are certain areas in which they take the value zero. In these areas, no eddy current is driven by the considered space component in a metallic foreign object. If the considered spatial direction is at the same time the one in which the sensor coil can be stimulated, then the foreign object is not detectable in these areas. An exception are objects made of ferromagnetic materials, such as iron, which conduct magnetic flux due to their very low magnetic resistance and thus can boost magnetic fields in their immediate vicinity. For these reasons, in this demonstrator, sensors will be characterized based on their ability to detect metallic foreign objects in the magnetic field. Since the detectability of foreign objects depends on their material composition as well as their size and shape, test objects as described in SAE J2954 (2020) and DIN CLC IEC/TS 61980-3 (2021) are used. Another parameter for detection is the position of the foreign object in relation to the ground assembly coil and the sensor coils. Therefore, the detectability is evaluated depending on the position of the foreign object. In order to consider symmetry influences, sensor coils of different sizes and shapes are characterized. The practical measurements already carried out show the potential of passive inductive sensors for FOD. The publication of the results is currently being worked on. Based on the practical measurements, simulations for the detection of metallic foreign objects are carried out, which then form the basis for the virtual development and validation of such systems in the near future. This provides practical proof of the functionality of the sensor coils and the detection method in laboratory tests and simulations. The technology readiness level (TRL) of this demonstrator is 3.

From the charging system perspective, the detection of metallic foreign objects represents a safety-relevant functionality which should be carried out for every power transmission according to SAE J2954 (2020). Therefore, this functionality should not only be assessed during development and production, but should also be able to be monitored throughout the charging system's service life. This means that tests are required which can be executed at runtime and which provide information about the current functionality of the individual components of the FOD system.

4. Demonstrator 2: robust physical perception sensors

The aim of demonstrator 2 in SC1 is to avoid forwarding incorrect sensor data to the system enabling a more robust understanding of the surrounding. With respect to the usage cycle, the application of this demonstrator lies in the improved handling of the dynamic driving task as well as supporting extensions to future ODDs. Within this demonstrator, different levels of the perception processing chain (fused sensor data in Section 4.1 and the individual sensors in Section 4.2 and respectively in Section 4.3) are monitored and analyzed for sensor faults. Besides the consideration of internal faults, the analyzed faults include adverse weather effects and other environmental factors such as sensor cover damages as well as interference effects from other sensors (e.g., cross talk in radar sensors).

4.1. Fused sensor data: sensor faults detection and mitigation

No sensor can operate reliably under every condition. Also, it is not guaranteed that the performance does not de-grade over the lifetime of the sensor. All perception algorithms rely on the input data provided by respective sensors; so, it is crucial to be aware of the current reliability of measurement data (Kalra and Paddock (2016)). Since an experiment cannot be conducted over the complete lifetime of an ECA, a dataset was captured from a real environment. It contains numerous difficult rainy and snowy situations when failures of sensors occurred due to harsh weather conditions (Ligocki et al. (2022)). More than 3 hours of data were captured simultaneously from all the sensors during a journey of about 120 km. The data contains LiDAR freezing, camera lenses covered with water drops, freezing water drops, snowflakes, and slices of ice. The major part of a dataset has been captured during the night and with activated street lighting. This dataset is used for developing fault detection algorithms and training of artificial intelligence algorithms.

The fusion-based fail-detection system is briefly described in Fig. 2. Each block is then further explained in the following paragraphs.

Reliability self-assessment: The basic sensor failures for cameras can be primarily estimated by applying statistical methods to captured data, overall image brightness, image sharpness, or optical flow when a vehicle is in motion. For other sensors, like LiDAR's, the number of measured points and corrupted measurements is tracked. This process provides an initial guess of sensor output reliability.

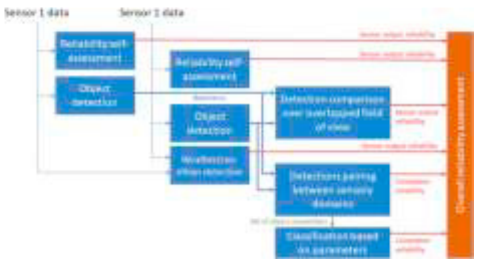

Fig. 2. Block diagram of a fusion-based fault detection system

Detection comparison: The other approach to detect sensor failure is to track the detections within overlapping field of view of more sensors. If there is a significantly lower object detection rate of a sensor compared to the others, it may be an indicator for sensor failure. The object detections can be repaired between the same sensors (e.g., left RGB camera and right RGB camera), but also in pair of RGB and IR cameras under certain conditions (see next paragraph).

Weather/condition detection: Another use case are bad weather or light conditions when the infrared camera data could have better reliability than the RGB ones. Once this situation is detected, higher trust is put on the sensor with currently better performance. Another combination could be object detection based on the LiDAR sensor, which deals better with the rain compared to the cameras.

Detection pairing: The next step is a neural-network-based comparison of the detections between the sensor domains based on pairing in a spatial area. The primarily focus is put on comparing the classes and object dimensions across the sensor domains and statistical markers over the gathered data. Since some classifications are sensor dependent (e.g., the shape is better to be recognized from LiDAR data, but color is accessible from RGB camera only), the cross-correlation of detections leads to merging the sets of parameters, thus creating the more specific description of object. This decision is more reliable than using the sensors separately.

All the reliability information is then combined in the overall reliability assessment block. It provides the reliability of assessments (detection, classification) to the higher level system, which uses the data for further decision making. The current estimated TRL is 3.

4.2. Sensor: LiDAR, fault: mechanical damages

Understanding the influence of LiDAR faults on sensor data is essential for increasing perception robustness of automated vehicles since fault information can be forwarded to sensor fusion algorithms in order to reduce trust in faulty sensors. The survey paper of Goelles et al. (2020) gives an overview of perception sensor faults and their classification which is a good basis for choosing sensor faults to investigate with the demonstrator.

Fig. 3. Ouster OS1 with 64 lines in vertical direction and the transparent cover

For the investigation of the influences of LiDAR faults on sensor data, we use a LiDAR demonstrator for static measurements that consists of an automotive LiDAR, the Ouster OS1-64, which is mounted on a tripod. We added transparent cover to the LiDAR to apply faults to this cover like damages without damaging the original sensor cover (see Fig. 3). We use a squared retro-reflective target to have a known ground-truth. The demonstrator was introduced by Schlager et al. (2021) where it served for testing the influence of faults, e.g., mechanical damages of the sensor housing, on output data of the LiDAR. The LiDAR data is recorded with the Robot Operating System (ROS) driver that is provided by the manufacturer and is post-processed with the Python package “pointcloudset” Goelles et al. (2021). First results presented in Schlager et al. (2021) show that the distance between the points measured by the LiDAR and an ideal plane increases if mechanical damages are applied to the cover. We plan to use the demonstrator for further investigations on the influence of other LiDAR faults on LiDAR data. The current estimated TRL of the demonstrator is 3.

4.3. Sensor: radar, fault type: cross talk

Mutual interference is bound to become a safety-critical hazard for the operation of radars, in particular when considering higher-level ADAS/AD functions (Kunert et al. (2010)). Interference can be of a very high power and mask objects. A reliable detection of traffic objects is necessary. This requires a quantification of sensor performance and reliability in interfered traffic scenarios. Furthermore, interference should be detected and optimally also mitigated at the sensor level.

Interference appears in the raw signal received by the sensor; hence, a low-level model of the sensor and the received signals is necessary to properly describe the phenomenon. In particular, we focus on the industry standard frequency modulated continuous wave radar (FMCW) radar sensors. To this end, a simulation framework is implemented that is capable of generating an arbitrary scenario of objects and interferers. The received signal is then processed by a conventional range-Doppler processing chain, with added optional interference detection and mitigation steps. The output of the sensor is then the list of detected objects with their range, velocity, and angle values. In an interfered environment, the sensor will generally have impaired object detection sensitivity. The applied signal models can be found in Kim et al. (2018); Toth et al. (2018), among others. From the signal modeling efforts, a variety of different methods for interference mitigation can be proposed. These make use of properties of the signal components in the different domains, and hence can be characterized and catalogued in different ways, e.g., according to the domain or where they are placed in the processing chain. For more information, we refer to cited documents Rock et al. (2021); Engels et al. (2021) and references therein. There is a vast variety of traffic and interference scenarios to consider for validation, which a limited selection of evaluations may not cover. Hence, it is most reasonable for validation to use a Monte Carlo-based statistical evaluation framework. Fig. 4 depicts this framework. A large set of configurations is defined, which contain all parameters setting the traffic scenario, sensor, and processing parameters as well as the interferers. All instances of this configuration are then loaded and processed, and certain metrics are computed that evaluate the behaviour of the sensor. Finally, the metrics from all evaluated scenarios are grouped and analyzed in terms of their statistical distribution. Some results of applying our framework can be found in Rock et al. (2021); Toth et al. (2021).

The evaluated scenarios may be purely simulated, measurements, or a combination of both. Current measurement datasets consist of a large number of radar measurements conducted on the streets of the city of Graz. Besides this comprehensive analysis framework, promising interference mitigation algorithms are also implemented on hardware for real-time demonstration purposes, an example of which is seen in Fig. 5. Hence, a TRL of 5 is estimated.

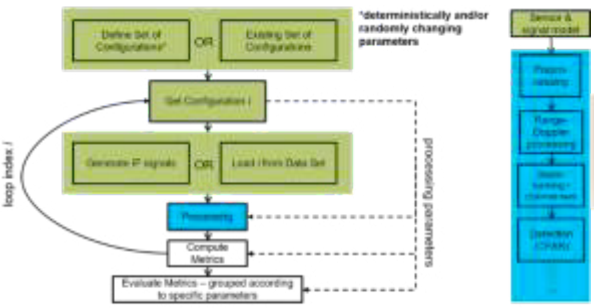

Fig. 5. Mitigation demonstration on an Infineon Pico Radar

Fig. 4. Block Diagram of Framework Implementation

5. Demonstrator 3: position enhancement using 2D cameras

This proof of concept demonstrator aims to enhance the position calculation of a vehicle using 2D front camera images, inaccurate global positioning system (GPS) coordinates of the vehicle and accurate GPS coordinates of traffic lane boundaries. With respect to the usage cycle, this demonstrator also addresses the dynamic driving task. It increases positioning robustness in areas where GPS signal is weak distorted (e.g., urban canyoning, valleys, tunnels). The exploitation potential of such technology is huge due to the high number of front cameras equipped already available in middle and high class vehicles. Three algorithms are used within the demonstrator (see Fig. 6): Algorithm 1 takes the GPS coordinates of the vehicle and the GPS coordinates of the traffic lane boundaries and outputs the GPS coordinates of the traffic lane boundaries closest to the given GPS coordinates of the ego vehicle. Algorithm 2 takes in an RGB image and returns the relative position of the car within the traffic lane boundaries. This is done by first segmenting the image using a deep neural network (Ronneberger et al. (2015)) to identify the traffic lane boundaries. Afterwards, the relative position is computed as the distances from the left and right road boundaries to the middle pixel of an image, which is assumed to be the location of the vehicle in the image. Finally, Algorithm 3 takes the outputs of Algorithm 1 and 2 to output accurate GPS coordinates of the ego vehicle.

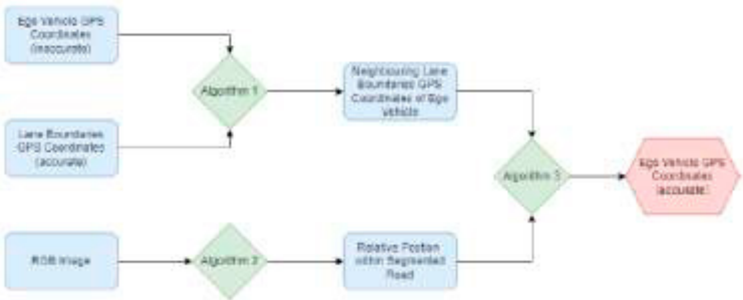

Fig. 6. position enhancement process chart

4. Conclusion and outlook

Failures in the acquisition and perception system, that may be caused by internal errors or uncertainties of the associated sensors as well as by the subsequent data processing pipeline, may result in hazards and risks for human life. The detection of different failures of the perception and acquisition system along a typical ECA usage cycle (charge - drive - restart charging) was introduced in this paper. Each demonstrator addresses specific steps of this typical ECA usage cycle.

Utilizing a FOD solution before and during charging, a safety-relevant subsystem of a wireless charging system is investigated. This improves safety and high reliability of the overall system and a high end-user trust. However, such systems must be functional not only after production, but throughout their entire service life. The robust physical sensor demonstrator shows how fault detection supports the dynamic driving task at the level of the individual sensors but also in terms of the fused sensor data by identifying different sensor faults. The robustness and reliability of physical environmental perception systems is then improved while driving. The demonstrator on position enhancement, which uses a 2D camera and information on the lane positions, enables a fail-operational behaviour as it allows to continue the dynamic driving task, even when the GNSS signal is lost. When used in conjunction with GNSS, it can improve the positioning accuracy by adding an additional (lane-level) source for position information. For the individual demonstrators, journal publications are in preparation providing in-depth insights on results, methodologies and KPI evaluations.

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