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Multisensor Avionics Architecture for BVLOS Drone Services

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Abstract. This ADACORSA demonstrator focuses on the implementation of a fail-operational avionics architecture combining Commercial Off-The-Shelf (COTS) elements from the automotive, the aerospace and the artificial intelligence world. A collaborative sensor setup (Time-of-Flight camera and FMCW RADAR from Infineon Technologies, stereo camera, LiDAR, IMU and GPS) allows to test heterogeneous sensor fusion solutions. A Tricore Architecture on AURIX$^{\mathrm{TM}}$ Microcontroller supports the execution of safety supervision tasks as well as data fusion. A powerful embedded computer platform (NVIDIA Jetson Nano) accelerates AI algorithms performance and data processing. Furthermore, an FPGA enables power optimization of Artificial Neural Networks. Finally, a Pixhawk open-source flight controller ensures stabilization during normal flight operation and provides computer vision software modules allowing further processing of the captured, filtered and optimized environmental data. This paper shows various hardware and software implementations highlighting their emerging application within BVLOS drone services.

1. Introduction and Motivation

Unmanned Aerial Vehicles (UAVs), commonly known as drones, are aircraft vehicles that are not operated by an onboard human pilot but can either fly autonomously or be remotely piloted. In the past few years, drones have received growing attention from diverse communities (e.g., academia, consumer electronics, mobility industry) due to their large spectrum of applications, ranging from logistics to surveillance through entertainment and agriculture.

In this context, the Airborne Data Collection on Resilient System Architectures project (ADACORSA) [1] is aimed at the development of the technical components (hardware and software) that enable the drones to perform Beyond-Visual-Line-of-Sight (BVLOS) services in the civilian domain. Within a consortium of about 50 partners, Infineon Technologies Germany and Infineon Technologies Austria, in collaboration with the University of Applied Science Technikum Wien, are working on creating a multi-sensor drone architecture demonstrator to benchmark Sensor Fusion algorithms.

Sensor fusion is one of the critical aspects of autonomous drone navigation since several tasks, such as obstacle detection and avoidance, self-state estimation, and flight stabilization, require combining information from diverse sources.
Although the state of the art is rather vast in terms of hardware components (sensors and computation platforms) and software architectures, the problems related to sensor fusion in autonomous navigation are yet to be solved [2, 3]. In addition, the correct functioning of the different sensor fusion solutions needs to be tested on a hardware drone architecture, preferably with actual flight tests. Therefore, a suitable flight hardware architecture must be available, equipped with a suitable set of sensors and edge computers.

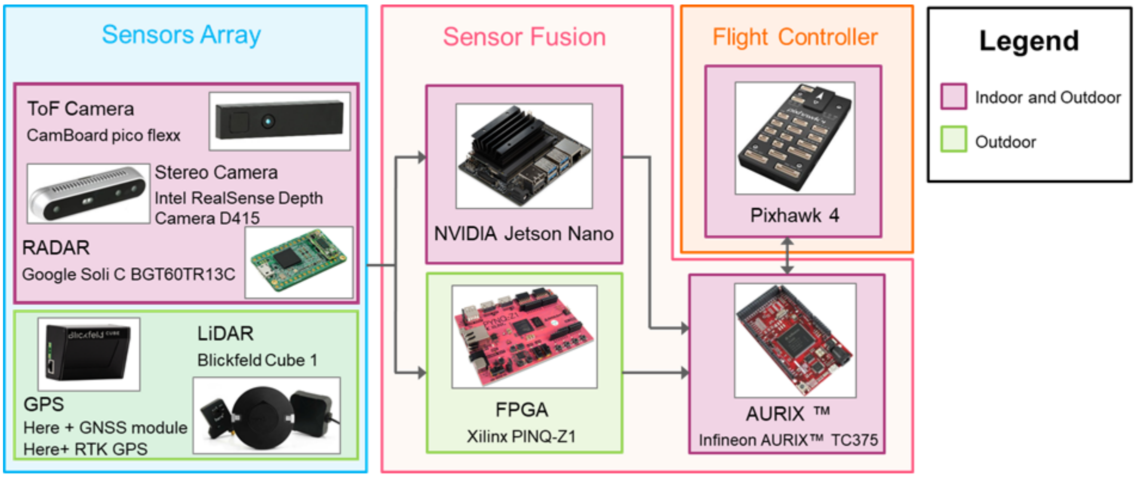

Figure 1. Overall Architecture Schema. The elements included in both sub-demonstrators are highlighted in purple, while the elements highlighted in green are only leveraged in within the outdoor demonstrator.

A survey of flight demonstrators developed between 2001 and 2006 in the context of military applications is shown in [4]. Such demonstrators mainly consist of GPS-enabled autopilots validated with Hardware-in-the-Loop simulations for sensor outputs and communication. More recent works are presented in [5], [6], and [7]. The former proposes a customizable architecture for rescue scenarios, while the latter two showcase examples of hardware architectures equipped with an IMU and a GPS sensor validated respectively with Software-in-the-Loop simulations and real flights for meteorological studies. Additionally, [8] presents a more complex architecture equipped with a Jetson Xavier computer for AI applications validated in multiple real flight scenarios. Finally, a few examples of drone demonstrators equipped with exteroceptive sensors are discussed in [9, 10, 11, 12]. In more detail, the work described in [9] consists of a stereo camera-aided system tested on a ping-pong play scenario. In [10] a camera-equipped flight demonstrator with a self-localization and target detection system is presented. The work presented in [12] proposes a search-and-rescue (SAR) drone demonstrator equipped with a RADAR sensor for object detection and GPS for pose estimation. Finally, in [11] sensor fusion with an RGB camera and a thermo camera is performed for object detection.

The state-of-the-art review showed that a fair amount of reference architectures is currently available. However, the amount and the type of sensors they are equipped with make them scenario-specific in most cases. On the other hand, when implementing a new demonstrator, the optimal set of sensors might not be known; therefore, real flight tests might be necessary to determine which type of information is the most suitable to carry out the navigation efficiently. Moreover, in most state-of-the-art architectures, tasks such as target detection are carried out with the help of a single sensor, which reduces the functionality of the system to a single-point-of-failure.

In this paper, we discuss the current progress in the implementation of a multi-sensor fail-operational avionics architecture for BVLOS drone services. The primary goal of the hardware architecture is to serve as a benchmark tool for various sensor fusion algorithms in the context of autonomous navigation. A collaborative sensor setup (Stereo Camera, Time-of-Flight camera, RADAR, LiDAR, GPS, and IMU) allows information fusion from different sources. Furthermore, the architecture is equipped with three embedded computing platforms enabling the execution of algorithms with different computational demands. First, an NVIDIA Jetson Nano can be exploited to execute AI applications. Secondly, an FPGA supports the execution of power-optimized applications. In addition, an AURIX$^{\text{TM}}$ Microcontroller supports the execution of sensor fusion algorithms as well as safety supervision tasks. Finally, a Pixhawk 4 serves as a flight controller and offers computer vision software modules.
The architecture can be easily adapted to fit different scenarios. Two different adaptations are currently being developed as part of this demonstrator. The first one targets outdoor scenarios with forest monitoring and last-mile delivery as reference use cases. It includes the whole sensor setup and the three computing platforms. It currently supports the creation of a dataset, the deployment of Artificial Neural Networks for object detection, and the acceleration of Simultaneous Localization and Mapping (SLAM) algorithms.
On the other hand, the other version addresses indoor scenarios with construction site surveillance and indoor logistics as reference use cases. This version does not include the GPS and LiDAR sensor nor the FPGA. The adapted architecture has been mounted on a DJI 415 Flame Wheel allowing for a real-flight detect-and-avoid demonstration.

Figure 2. Hardware architecture for indoor flight mounted on DJI-415 Flame Wheel.

The remaining of the manuscript is organized as follows. Section 2 gives an overview of the components present in the architecture and the algorithms running on the embedded computing platforms. Section 3 describes how the implementations in Section 2 are utilized for indoor and outdoor navigation scenarios. Finally, Section 4 draws the conclusions.

2. ADACORSA platform demonstrator

This section describes the avionics architecture schematized in Figure 1. As mentioned in Section 1, two different customizations of the architecture have been considered for its design. One of them, which includes all the elements schematized in Figure 1, is targeted at solving outdoor scenarios problems, while the other (Figure 3) , targeting indoor environments, exploits only part of the sensor setup and is specific for indoor environments. Also, the latter does not consider FPGA support for Artificial Neural Network processing. This decision is supported by the increased complexity of the object detection task in outdoor environment, which raises the problem of power resources optimization for the computing platform. A preliminary version of

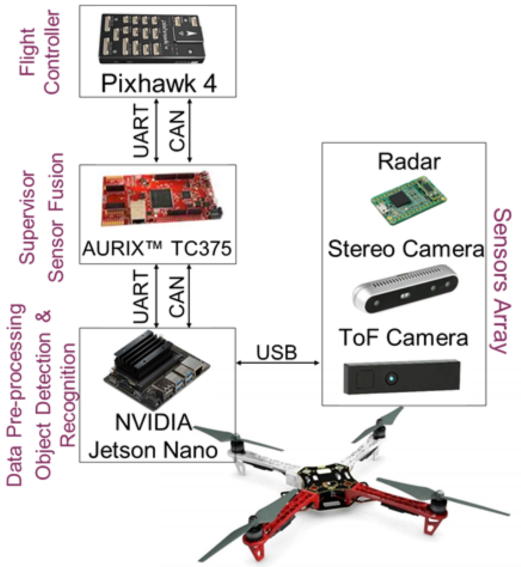

Figure 3. Indoor Demonstrator Schema

the outdoor variant was mounted on a cycling helmet to support data acquisition in no-fly areas, while the indoor variant has been mounted on a DJI-415 Flame Wheel (Figure 2) in order to carry on real flight tests.

2.1. Environmental Sensors

The architecture is equipped with a collaborative sensor setup, conceived to guarantee redundancy and fail-operationality. The available sensors are:

- Stereo Camera (Intel Real Sense D450 Stereo Camera) providing visual and depth information in the range of 4 meters.
- Time-of-Flight Camera (pmd Pico Flexx) providing a point cloud in a range of 4 meters.
- LiDAR sensor (Blickfield Cube 1) providing a point cloud in a range between 4 and 11 meters, so that a point cloud in the range 0-11 meters can be obtained by combining its information together with the ToF camera.
- FMCW RADAR (Google Soli-C) providing position and velocity information of moving targets.
- GPS module with Real-Time-Kinematics (RTK) receiver (Here+) providing positioning information with cm-level precision.
- IMU (integrated into the flight controller platform) providing inertial information.

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The sensor setup can be customized to adapt to the needs of each use case scenarios. For instance, the customization for indoor scenarios proposed in this paper makes use of Stereo Camera, ToF camera and RADAR sensors for object detection and avoidance, while the one for outdoor scenarios, in its final version, will exploit the whole sensor setup for self pose estimation and object detection.

In both demonstrators, a custom 3D-printed support was designed and mounted on a helmet in the case of the outdoor demonstrator, and on a DJI-415 Flame Wheel in the case of the indoor demonstrator, as shown in Figure 4.

Figure 4. Preliminary setup for data acquisition. 3D printed support located on the helmet

2.2. Environmental Sensor Data Platform

This section describes data gathering and drone's Artificial Intelligence perception mechanisms: Most of the algorithms targeting at this problem are implemented in the NVIDIA Jetson Nano parallel architecture with the goal of accelerating data processing·

Data gathering for outdoor scenarios. The NVIDIA Jetson Nano supports the acquisition of a multimodal dataset for the validation of SLAM and object detection algorithms. To the current state, the embedded platform is receiving data from the entire sensor setup, with the exception of the LiDAR sensor, with a frequency of 10 Hz. The acquisitions are taking place at the Infineon Technologies AG headquarters located in Munich, which offers a diverse mix of environments, such as urban, forestry and open field. The collected data is being stored and organized according to the well-known format of the ASL dataset [13]. The inclusion of the LiDAR sensor, due to its significant computational power requirements in the environment perception stage, currently results a significant decrease in the acquisition frequency. Further optimizations in the code and in the sensor configuration might improve the overall performance.

Simultaneous Localization and Mapping for outdoor scenarios. IMU and LiDAR-aided Simultaneous Localization and Mapping (SLAM) is being deployed on the NVIDIA Jetson Nano. In particular, a parallelized version of FastSLAM2.0 [14] exploiting GPU features is being developed. This is aimed at providing centimeter-level precision pose estimation as well as an environmental map reconstruction.

Object recognition for outdoor scenarios. The NVIDIA Jetson Nano executes camera-aided object detection algorithms for outdoor scenarios. A pre-trained model called SSDmobilenetv2 [15] is deployed and is able to identify the following targets: bike, person, building, tree, and fence. Efforts are being put towards the mapping of the RADAR, LiDAR and ToF camera data onto the camera images.

Object detection and recognition for indoor scenarios. In the context of the indoor demonstrator, a multi-sensor object detection and recognition system is being developed based on stereo camera, ToF camera and RADAR. Both the stereo camera and the ToF camera provide a video stream in addition to the stereo images and the point cloud stream. SSDMobilenetv2 identifies various targets (person, table, screen) based on these video streams. Moreover, the position vectors of each target is calculated by mapping the depth information coming from the stereo camera and the ToF camera. On the other hand, RADAR sensors can only provide position information of each target without any label. Therefore, the position vector of each target is matched with the closest object detected by the stereo camera. The three position vectors are then passed to the AURIX^{TM} Microcontroller as shown in Figure 5. The sensor fusion algorithms performed by the AURIX^{TM} is discussed in Section 2.4.

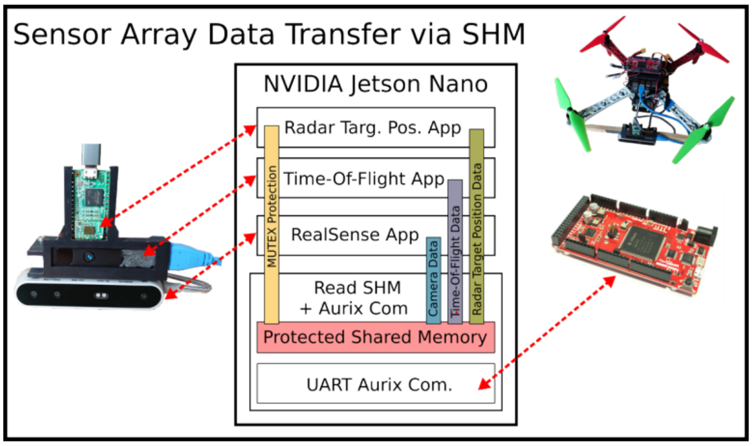

Figure 5. Sensor array data transfer via shared memory.

2.3. Hardware Co-Design Power Optimization

The NVIDIA Jetson Nano is a powerful tool to deploy sensor fusion algorithms in a fast and flexible way. However, autonomous drone solutions might have, in some cases, critical requirements related to time-constrained processing and limited power consumption. Unfortunately, these two aspects have limited range of optimization in boards designed for general purpose. On the other hand, the use of configurable devices offers the possibility to improve the performance in terms of computation time and power consumption through specific designs and architectures. Thus, the avionics architecture includes an FPGA to support the research on hardware co-design and optimization for high power demanding applications. This approach is particularly beneficial when hardware parallelization of the algorithms is possible, as with most of the Artificial Neural Networks (ANNs) topologies. For this reason, the first efforts have been focused into the creation a framework to train, optimize, and implement ANNs on FPGAs, as presented in [16]. The goal of this framework is to provide highly certified and sustainable solution for resource and energy-constrained devices.

2.4. Sensor Fusion Algorithms on AURIX^{TM} Microcontroller

A Multicore Software Architecture on AURIX^{TM} Microcontroller is currently available for the indoor demonstrator. Its Tricore hardware architecture enables the execution of three different tasks in parallel. One of the cores (core #0) is in charge of periodically retrieving the coordinate vectors of each detected target and to transmit them to a second core (core #1). Core #1 is indeed in charge of carrying out sensor fusion tasks. In more detail, the three coordinate vectors (coming from RADAR, Camera and ToF camera) feed a Triple-Modular-Redundancy (TMR) voter, which is in responsible for detecting any failure: three target detection values are constantly monitored on any data inconsistency. The resulting value of the TMR feeds, in turn, an axis-oriented Kalman Filter. The filtered values are then sent as MavLink messages to the flight controller. Within the last core (core #2), a supervisor task observes different internal execution steps and provides debug information via the onboard USB/Serial interface of the AURIX$^{\mathrm{TM}}$ Microcontroller. It checks whether the other two cores are alive, as well as the NVIDIA Jetson Nano and the Pixhawk. Then, data regarding the Kalman Filter Parameters and the coordinate vectors are collected and showed on screen.

2.5. Pixhawk Flight Controller
An off-the-shelf flight controller software is running on a Pixhawk4. The open source Ardupilot Software Suite is in use. The application can run on the NVIDIA Jetson Nano and offers a variety of features including semi-autonomous and fully manual flight mode, Software-in-the-Loop (SITL) simulation and support for navigation sensors such as IMU and RTK GPS. Additionally, ArduPilot offers a user interface which allows to visualize the drone location as well as to set waypoints for trajectory planning.

3. ADACORSA Platform Demonstrator Outdoor and Indoor Use Cases
The variety of available sensors and computing platforms allows the architecture to adapt to several use cases in both indoor and outdoor scenarios. On the one hand, the outdoor platform customization targets two different use cases: forest monitoring and last-mile delivery. Being equipped with a high precision GPS sensors and, in its final version, with a localization system based exclusively on LiDAR and IMU, it will easily adapt to GPS-denied environments, such as urban scenarios (canyoning due to high buildings or underpasses may affect the quality of the GPS signal). Furthermore, the presence of both long and short range sensors enables the detection and avoidance of targets at different distances (i.e., birds, people, trees, other drones). Finally, the architecture can be mounted on different drone structures in order to handle different payloads. On the other hand, the indoor demonstrator targets drone-aided construction sites and indoor logistic services. In this type of scenarios, where relevant targets are generally located within a shorter range, the ToF camera, the Stereo Camera and the RADAR sensors provide sufficient information to detect and avoid obstacles without the need of a heavy and power demanding sensor such as the LiDAR.

4. Conclusion and Discussion
In this paper, we have introduced a multisensor avionics architecture for BVLOS drone services. The architecture aims to support the validation of sensor fusion algorithms that perform various tasks in the context of autonomous navigation, such as object detection, self-pose estimation, and data gathering. We have highlighted the key features of the sensor setup and the computing platforms, as well as the current status of the available implementations running on them. The architecture setup can be easily customized in order to adapt to different use case scenarios. In more detail, we proposed two possible variations: one targeting outdoor environments (last-mile delivery and forest monitoring) and one intended for indoor navigation (e.g., construction sites).

The future steps in the development of the outdoor architecture include:

- Increase in the frame rate for data gathering
- Completion of the implementation of the SLAM software architecture
- Extending the capabilities of the presented ANNs framework for FPGAs by including new optimized topologies.
- Adaptation of the Multicore software architecture running on the AURIX$^{\mathrm{TM}}$ Microcontroller for outdoor scenarios.

- Real-time validation, in real scenarios and/or Hardware-in-the-Loop (HITL) simulation.

while the next steps in the context of the indoor demonstrator are:

- Integration of Environmental Sensor Module (ESM) into Robot-Operating-System (ROS).
- Transfer of Multicore Microcontroller Firmware into PX-ROS (Real Time Operating System for multicore).
- Transition from LiDAR (static) point cloud to ESM (dynamic) point cloud Mapping.

5. Acknowledgments
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