Machine Learning Applications in Unmanned Aviation: Operational Risks and Certification Considerations

Figure 1: Unmanned cargo gyrocopter ALAADy-Demonstrator capable of carrying up to 50 kg of payload

ML Applications in Unmanned Aviation

With recent advances in machine learning (ML), new levels of autonomy for drones are achievable. The key application in this context is **sensor-based perception** of the environment, others include trajectory optimization, high-dimensional motion planning, adaptive flight **control** and anomaly detection. With these applications, ML is a key **enabling technology** for a set of mission scenarios that have been in the focus of recent research activities at DLR Institute of Flight Systems:

- Automated **aerial delivery** (e.g. in humanitarian aid),
- Urban air mobility (**UAM**),
- **Remote sensing** (e.g. in agriculture, environmental control, maritime security, infrastructure inspection)
- **Perimeter monitoring**
- Air-to-air **drone defense**

The unmanned cargo gyrocopter ALAADy-Demonstrator (Fig. 1) and the helicopter drone superARTIS (Fig. 2) are two examples of a fleet of **demonstrator platforms** operated at DLR Institute of Flight Systems to develop, integrate, and validate experimental AI-based avionics systems and technologies (see Fig. 4, 5 and 6 for examples) to increase the level of autonomy.

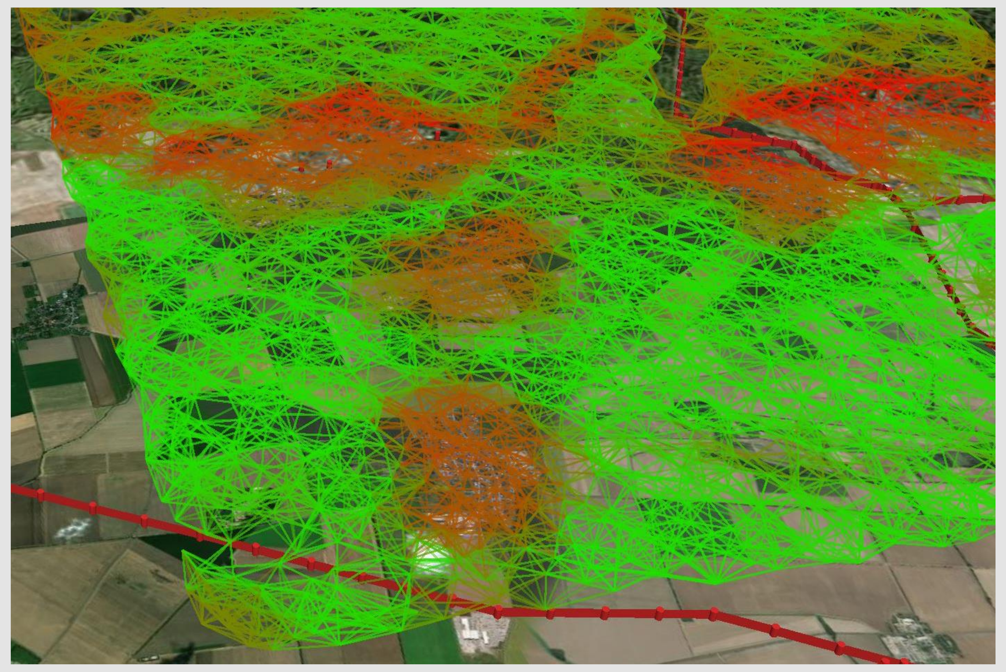

Figure 4: Sampling-based motion planning for unmanned aircraft in unstructured environments and considering complex cost functionals.

Figure 2: Unmanned helicopter superARTIS equipped with LIDAR and optical sensors for environment perceptions in autonomous flight

Operation-centric Certification and its Implications to ML-based Systems

The **key challenges** for applying ML technology in unmanned aircraft are related to **safety** verification and validation. There are on-going efforts of the aviation community to establish **new regulations**, means of compliance, and assessment techniques to prove the safety of **ML-based avionics** systems. However, the recent shift to operation-centric certification of unmanned aircraft, in particular the **Specific Operations Risk Assessment** (SORA), and its implications to ML-based technology have not yet been considered in this context. The concept of **operational constraints**, as proposed for the EASA specific category, could be leveraged to **lower the hurdles** of applying ML technology in drones without compromising safety. Based on the concept of a **risk-centric certification**, verification could be simplified by relying on certifiable **runtime monitoring** in order to guarantee compliance to operational constraints. In conclusion, novel risk-centric concepts in drone regulations and certifications, have the potential to fast-track the development and safe application of ML-based autonomy for unmanned aircraft.

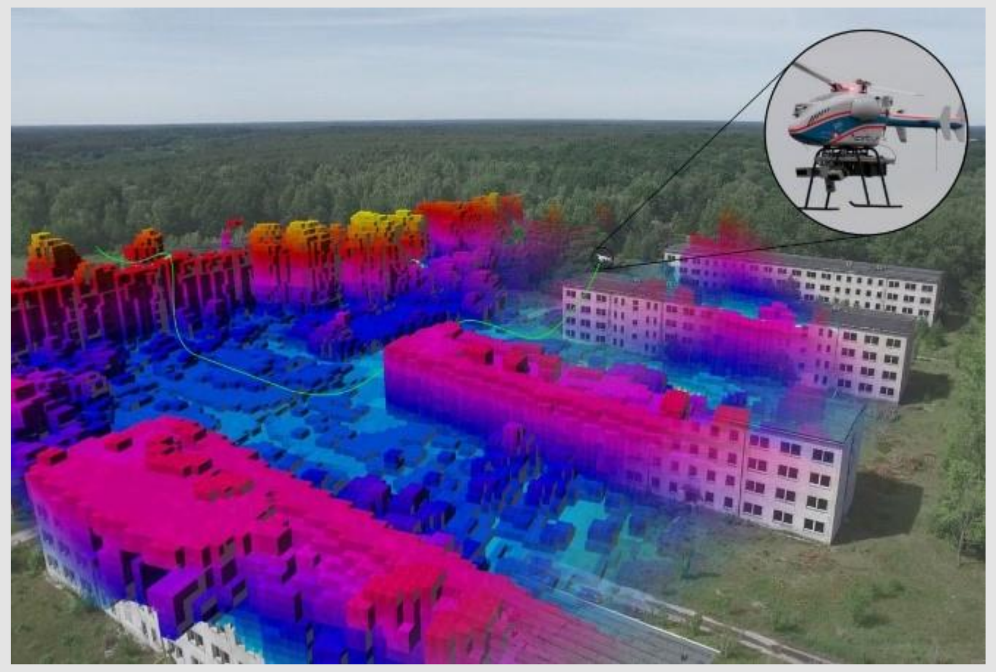

Figure 5: Autonomous navigation in a priori unknown environments using sensor-based environment perception.

Regulation and Standards for Safe AI

Existing standards and regulations for safety-critical systems in manned aviation demand rigorous verification and traceability of requirements which appears **inapplicable** to ML-based systems. This challenge is currently being addressed by authorities and research institutions in several on-going activities:

- identify and document challenges as a **common ground** for discussions (e.g. EASA AI Roadmap),
- involve relevant aviation **communities** and institutions, (EuroCAE WG-114, SAE G-34),
- standardize runtime monitoring as a means of containment and **AI safety risk mitigation** of otherwise unsafe systems (ASTM F3269 and revisions),
- tackle the challenge of **learning assurance** of neural networks (CoDANN),
- transfer concepts regarding ML safety and standardization from **other domains/industries** (e.g. ISO/PAS 21448, SOTIF from automotive),
- leverage operation-centric and risk-based certification approaches (SORA) to **lower the entry barriers** for ML in unmanned aviation through the application of operational constraints.

Risk Assessment

In order to apply ML as part of safety-critical functions, an adequate and applicable method to assess the operational risk of **failure or unintended behavior** is required. Risk analysis methods established in aviation rely heavily on statistical failure rates. How to assess such failure rates for ML-based avionics components is an open question. On the other hand, the **qualitative risk assessment** strategy defined by SORA is based on the definition of operational constraints – a concept which may be relatable to the idea of an **operational design domain** (ODD) of ML-based components. Finally, both qualitative and quantitative methods will have to be combined to properly assess the safety and remaining risks of ML-based avionics components.

Safety Assurance at Runtime

A key concept to protect against functional failures is to monitor the temporal behavior of a particular component's inputs and outputs at runtime with regard to a formal specification, also called runtime monitoring. Closely related is the concept of a **Safety Monitor** that assures compliance to the operational environment, reports violations, and consequently **triggers mitigations** (Fig. 3 shows an FPGA-based monitor used in flight test validation). As this technology is applied to operational constraints imposed by the SORA, it may also be applicable to ensure **compliance to ODDs** of ML-based components, e.g. restrictions to daytime or certain flight phases. This approach would allow to deploy highly specialized ML-based components with narrow ODDs without compromising system safety.

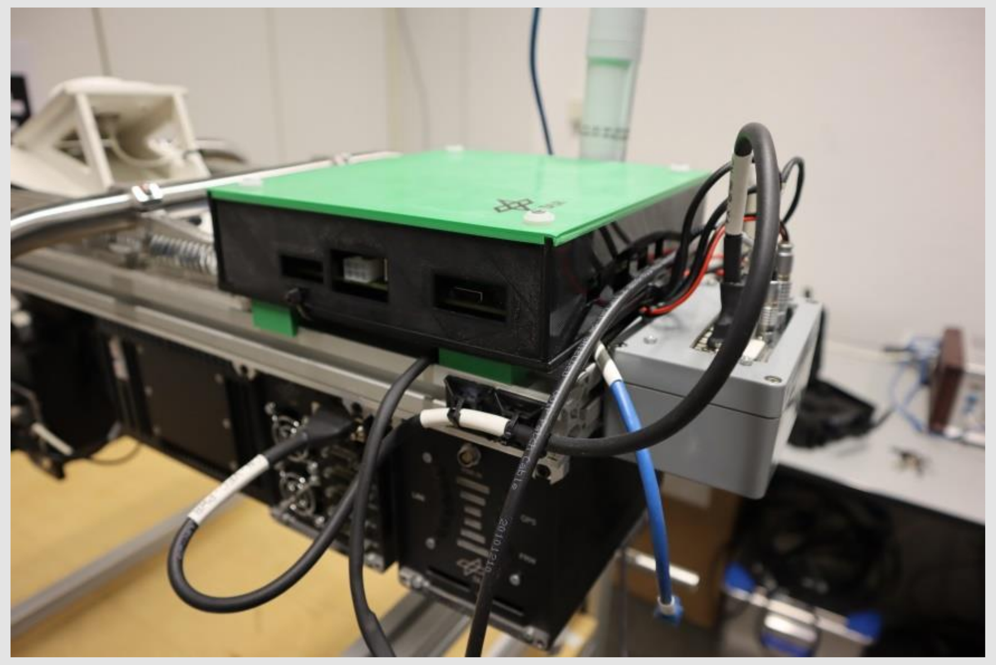

Figure 3: FPGA safety monitor on superARTIS experimental payload rack.

A System Integration Perspective on Verification of ML-based Autonomy

From a system integration perspective, three challenges remain for applying ML to autonomous drones without compromising safety:

- **Assessing the risk** of ML-based functions within avionics components and ML-based systems in an operational context. Which methods and models are applicable for this task?
- Minimizing the **risk of malfunction** through design assurance and verification techniques on avionics components level. How to assure the learning process? How to test ML-based components? How to measure and verify robustness?
- Mitigating the **operational risks** through runtime assurance. How to formally define and monitor the operational design domain as well as intended behavior of ML-based components?

At DLR Institute of Flight Systems these challenges are addressed from a holistic view on unmanned aircraft operations. The goal of our research is to contribute towards the safe integration of ML technology into drones to increase autonomy and enable new mission scenarios.

Figure 6: Synthetic training image for machine learning applications.

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