AI based Sense and Avoid System for Autonomous Flight

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INTRODUCTION

The increasing complexity and operational demands of modern helicopter missions, particularly those conducted in challenging and unpredictable environments, present significant risks that, when combined with inherent human factors, have contributed to a notable rate of accidents. Operations such as low-altitude flight in obstacle-dense urban settings, search and rescue in mountainous topography, and missions in degraded visual environments (DVE) push both crew and aircraft to their limits. The cognitive and physiological strain on pilots in these high-stakes scenarios can lead to errors in judgment, making the development of advanced automation and autonomy not just a matter of convenience, but an essential evolution for aviation safety. In this context, one of the most critical automated functions required to mitigate these risks is a reliable “Sense and Avoid” capability.

This paper describes a robust, multi-layered method for implementing an automated obstacle detection and avoidance system. Our approach leverages the power of artificial intelligence (AI) and advanced data/sensor fusion to create a comprehensive and resilient safety net around the aircraft. By integrating inputs from a suite of complementary sensors, such as radar, LiDAR, and electro-optical/infrared cameras, the system generates a high-fidelity, 360-degree model of the operational environment. This fused sensor data feeds into sophisticated AI algorithms capable of real-time threat assessment, distinguishing between static obstacles (e.g., terrain, buildings, wires) and dynamic traffic. Crucially, this includes an integrated anti-collision function designed for multi-asset scenarios, ensuring safe deconfliction with other friendly aircraft. The system is engineered to align with the European Union Aviation Safety Agency (EASA) roadmap for autonomy, supporting a scalable implementation from initial automation with a human in the loop—providing critical alerts and decision support—to eventual full autonomy where the aircraft can independently execute safe-haven maneuvers. Ultimately, this approach will not only serve as a powerful flight safety enhancer by drastically reducing the probability of collisions but will also significantly advance flight automation by bestowing a higher degree of intelligent autonomy upon the helicopter platform.

SENSE AND AVOID

The concept of "Sense and Avoid" is, without question, a cornerstone of aviation safety, and it is not a new topic. For decades, the aerospace community has dedicated substantial effort to developing systems that can detect and prevent mid-air collisions and impacts with terrain or obstacles. These foundational efforts, which we can term 'classical approaches,' were pioneering for their time and have formed the basis of current safety standards. Major research and development initiatives have been conducted by leading global entities. For instance, NASA has spearheaded numerous programs focused on the integration of Unmanned Aircraft Systems (UAS) into the national airspace, tackling key Detect and Avoid challenges. In Europe, projects like EUDAAS have been instrumental in defining the requirements for integrating Remotely Piloted Aircraft Systems (RPAS) into the broader air-traffic management framework. Concurrently, industry giants such as L3Harris, Airbus, and Leonardo have developed proprietary and often powerful sensor solutions and processing suites.

However, these classical systems, while effective in their intended domains, were often constrained by the technology of their era. They typically relied on a limited number of sensors, such as active radar or transponder-based systems like TCAS, which primarily addresses cooperative traffic. Their processing algorithms, with limited robustness (meaning that the processing gives good results in specific cases for which it is designed), were often based on conventional, rule-based logic that could be challenged in complex, cluttered, and dynamic environments—the very environments where helicopter operations are now becoming increasingly common.

This is where our approach marks a significant departure from the past and embraces a modern methodology. We are not simply proposing an incremental improvement or a more powerful sensor. Instead, we are leveraging the paradigm shift enabled by the convergence of two key areas: multi-modal sensor fusion and artificial intelligence. Our work capitalizes on the most advanced and recent technological breakthroughs to define a high-performance, truly intelligent system. By fusing data from a heterogeneous suite of sensors—like high-resolution radar, LiDAR, and multispectral cameras—we move beyond simple data aggregation to create a rich, comprehensive perception of the environment. This high-fidelity data becomes the fuel for sophisticated AI and machine learning algorithms, which can discern and classify non-cooperative air traffic and demanding obstacles like wires, with a level of reliability that was previously unattainable. This allows us to transition from a reactive avoidance system to a proactive and predictive safety function, paving the way for the next generation of autonomous aviation.

To graduate from classical methods and achieve a truly efficient and reliable Sense and Avoid capability, the system cannot be a niche solution. It must be a complete, robust system engineered to perform across the entire spectrum of helicopter missions and environmental conditions. A helicopter may be called upon to fly a low-level insertion mission in clear daylight and, hours later, perform a medical evacuation in fog and rain. A single sensor technology is simply insufficient to guarantee safety across such a diverse operational envelope. This inherent limitation of individual sensors is the primary driver for our adoption of a multispectral, multi-modal system architecture.

Our approach is founded on the principle of complementarity, where the weaknesses of one sensor type are offset by the strengths of another, offering therefore an excellent safety net benefit in the overall system. We propose a tightly integrated suite combining advanced optronics with radar systems.

- **Optronics**, which include high-definition cameras operating in several bandwidths (such as visible, near-infrared, and long-wave infrared), provide rich, detailed imagery that is exceptional for environment visualization, object classification and identification. This is crucial for example for distinguishing a non-threatening tree from a hazardous power line. This category also includes **LiDAR**, which uses laser pulses to generate precise, three-dimensional point clouds of the environment, enabling unparalleled accuracy in mapping terrain and detecting fine obstacles like wires. However, both cameras and LiDAR can be significantly degraded by adverse weather such as heavy rain, dense fog, or dust.
- **Radar**, on the other hand, excels precisely where optical systems falter. Its radio waves penetrate obscurants with ease, providing reliable detection and tracking of obstacles regardless of weather or time of day. It is exceptionally effective at measuring the range and velocity of moving objects, however offering lower resolution.

The critical enabling factor that makes this comprehensive fusion viable today is the continuous and dramatic improvement in the **SWaP-C (Size, Weight and Power - and Cost)** characteristics of these sensors. In the past, integrating such a diverse array of sensors onto a single, weight-sensitive platform like a helicopter would have been prohibitively complex, heavy, and expensive. Now, thanks to miniaturization and manufacturing advancements, it is possible to deploy a powerful, multi-modal suite that delivers a persistent, high-fidelity, all-weather understanding of the flight environment without compromising the aircraft's performance or mission capability.

Fig. 1. Example of IR cameras, Lidar and Radar for SAA

A fundamental principle of our system's design philosophy is its applicability to both civilian and military operational requirements. Our proposal aims at developing a core technological solution that is versatile enough to be adapted to the distinct challenges posed by each domain, ensuring a wider impact and a more sustainable development model.

On the civilian front, the need for advanced Sense and Avoid is accelerating. The rise of Helicopter Emergency Medical Services (HEMS), often operating at low altitudes and in un-surveyed landing zones, presents constant risks. Similarly, Search and Rescue (SAR) missions in a 4D (Dull, Dirty, Difficult, Dangerous) terrain, critical infrastructure inspection (e.g., power lines, pipelines), and the burgeoning field of Urban Air Mobility (UAM) all demand an unprecedented level of situational awareness to ensure safety. Our system provides the high-integrity perception needed to make these vital operations safer and more efficient, particularly in degraded visual environments. From a broader perspective, an obstacle detection and avoidance system is essential for all helicopter operations within a 4D operational environment.

The military need, while sharing the same fundamental safety goals, introduces unique specificities tied to mission-critical CONOPS (Concept of Operations). Military operations often involve deliberate flight in high-threat, non-cooperative environments where stealth and tactical maneuvering are paramount. The most demanding of these is Nap-of-the-Earth (NOE) flight, where helicopters fly as low as possible to use terrain for masking against enemy detection. This requires an exceptionally high-performance Sense and Avoid function capable of instantaneous threat detection and guidance at high speeds.

While NOE flight represents the pinnacle of system performance requirements, our approach leverages a modular, "technological brick" strategy. The foundational technologies developed and certified for less demanding civilian operations—such as sensor processing algorithms, object classification models, and data fusion engines—serve as robust, proven building blocks. These bricks can then be enhanced, hardened, and integrated to meet the stringent performance and environmental demands of military applications like NOE. This synergistic approach allows military development to benefit directly from the scale, investment, and maturation of the civilian sector, resulting in a more cost-effective, capable, and rapidly deployable Sense and Avoid solution for all users.

The Sense and Avoid function serves as a critical enabler for the broader goals of increased automation and, ultimately, full autonomy in aviation. It is a foundational building block upon which more complex autonomous behaviors are built. However, the implementation of such a function is not a one-size-fits-all endeavor. Therefore, a core component of our work will be a detailed study to define the necessary Level of Autonomy (LOA) required for the SAA system on both manned and unmanned platforms. This analysis is crucial because the true value of the SAA function is realized only if it demonstrably increases flight safety while simultaneously keeping the crew's cognitive workload under strict control, or even reducing it. An overly complex or "chatty" system, regardless of its technical power, can become a source of distraction and fatigue, thereby negating its safety benefits.

To determine the optimal LOA for any given flight, our approach will be context-sensitive, primarily considering two key factors: **Mission Complexity (MC)** and **Environment Complexity (EC)**. Mission Complexity relates to the number, type, and criticality of tasks the crew must perform, from simple transit to intricate multi-objective operations. Environment Complexity accounts for the operational setting, from a clear, open sky to a dense, obstacle-rich urban canyon in poor weather. By mapping these factors, we can define the appropriate level of autonomous assistance. For instance, a low-complexity mission in a simple environment may only require a basic advisory LOA, whereas a high-complexity mission in a complex environment would necessitate a higher LOA, where the SAA system can act semi-autonomously to manage threats. To formalize this process, a structured methodology like **ALFUS (Autonomy Levels for Unmanned Systems)** can be used, which provides a framework for evaluating and defining the human-automation task allocation across a spectrum of control.

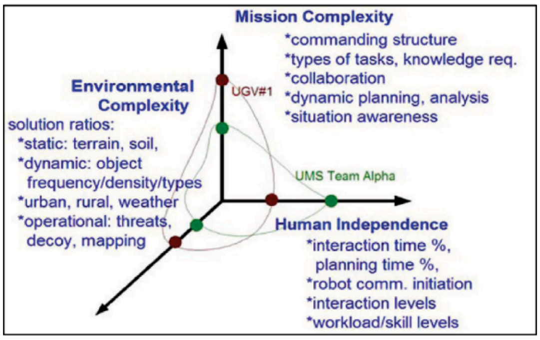


Fig. 2. Human Independence in the ALFUS Contextual Autonomy Capability (CAC) (ref. 3)

Achieving this delicate balance between capability and usability necessitates comprehensive studies and development focused on the Human-Machine Interface (HMI). The HMI is the critical link between the system's powerful sensing and processing capabilities and the pilot's perception and decision-making loop. Our design philosophy is centered on delivering the **right information**, at the **right place**, at the **right moment**, and in the **right shape**.

- **Right Information:** The system must intelligently filter and prioritize data, translating a deluge of raw sensor input into clear, concise, and actionable intelligence. Instead of displaying raw LiDAR point clouds, the HMI will present unambiguous obstacle identification and location.
- **Right Place:** We will investigate optimal methods for presenting this information, considering options from head-up displays (HUDs) and helmet-mounted displays (HMDs) for intuitive, eyes-out-the-cockpit integration, to decluttered symbology on primary flight displays.
- **Right Moment:** The timing of alerts is paramount. The HMI must provide sufficient warning for a safe maneuver without generating nuisance alerts during low-risk phases of flight.
- **Right Shape:** The format of the information must be instantly understandable. This involves developing intuitive symbology, such as color-coding for threat severity (e.g., yellow for caution, red for warning) and clear guidance cues, like three-dimensional pathways or avoidance vectors, that the pilot can follow.

To ensure our approach is grounded in certifiable standards, this entire analysis—from defining the autonomy levels to designing the HMI—will be based on EASA (European Union Aviation Safety Agency) recommendations and concept papers. By aligning our development with the regulatory framework, we ensure that the SAA function will be assigned an appropriate level of authority and that its interaction with the flight crew meets the highest standards of safety and human factors engineering.

Level 1 AI : assistance to human	Level 2 AI : human/machine teaming	Level 3 AI : more autonomous machine
•Level 1A: Human augmentation •Level 1B: Human cognitive assistance in decision and action selection	•Level 2A: Human and AI-based system cooperation •Level 2B: Human and AI-based system collaboration	• Level 3A: The AI-based system performs decisions and actions, overridable by the human. •Level 3B: The AI-based system performs non-overridable decisions and actions.

Fig. 3. Definition of levels of autonomy by EASA (ref. 5)

USE OF AI FOR SAA

AI and Data-Centric Development for Vision-Based Sensing

The recent emergence of powerful vision-based AI models, combined with the availability of compact, high-performance embedded computing capabilities, has made Artificial Intelligence a key enabler for creating the next generation of robust and performant SAA systems. For example, computer vision models based on deep learning have demonstrated extraordinary capabilities in object detection and semantic segmentation. Our methodology intends to systematically define and develop the main characteristics of an AI-based vision component for the SAA function. It's important to note that, for safety-critical applications, the current regulatory landscape, as outlined in EASA concept papers (see ref. 2), primarily covers **supervised AI**. This focus on supervised learning has a profound consequence: it places the creation and management of data at the very center of the development and certification process.

Consequently, **dataset creation becomes a key pillar** for the learning, validation, and verification of the AI models. These datasets must be meticulously curated to be representative of the full range of operational scenarios. They must be compliant with the typology of non-cooperative obstacles the system needs to detect—from power lines and towers to birds and other aircraft—and with the complete typology of the environment around the aircraft. This includes variations in terrain (mountains, urban, maritime) and a wide spectrum of meteorological and lighting conditions.

The primary tool that will allow us to tackle this complex data challenge is the **Operational Design Domain (ODD)**.

OPERATIONAL DESIGN DOMAIN

The ODD provides a formal framework for defining the specific conditions under which the SAA function is designed to operate. By methodically defining the ODD, we can systematically identify all required Operating Parameters (OP) data range, guide the data collection and generation efforts (using both real and synthetic data), and ultimately ensure that the AI models are trained and tested against a dataset that comprehensively covers their intended operational environment, for a given concept of operation (CONOPS), as defined in the EASA concept paper (2):

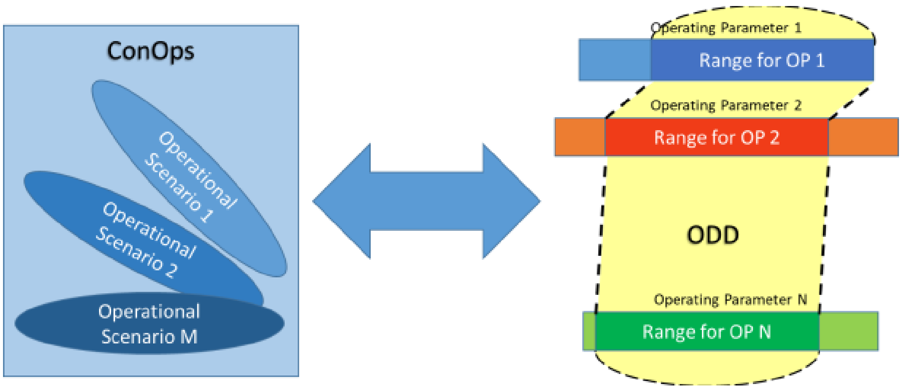


Fig. 4. Interrelationship between ConOps and ODD

The performance, reliability, and ultimate certifiability of the AI models are inextricably linked to the quality and thoroughness of the Operational Design Domain. A well-defined ODD acts as the master blueprint against which the dataset's completeness is assessed; it is not enough to simply have a large dataset, the data must be strategically aligned with the defined operational parameters. The first critical step is to constitute an adequate ODD which meticulously maps all flight conditions, environmental factors, and the specific performance characteristics of the onboard sensors.

In parallel with the ODD definition, an iterative dataset building process is undertaken to achieve comprehensive coverage of all potential obstacles. Recognizing that collecting sufficient real-world data for every possible scenario is impractical and often dangerous, our methodology champions a hybrid data strategy. This approach combines high-quality, real-world sensor recordings with data from high-fidelity **simulation** and in the future **generative AI**. Simulation allows us to create rare but critical "edge-case" events on demand, while generative AI can produce vast quantities of varied, photorealistic data to augment specific, underrepresented categories within the dataset. As an example, to train a model to detect wires, real LiDAR point cloud data from flight tests can be significantly augmented by simulated point clouds of various wire configurations and tensions. This ensures the AI model learns to generalize from a much richer set of examples than could be collected through physical tests alone, dramatically improving its robustness and reliability.

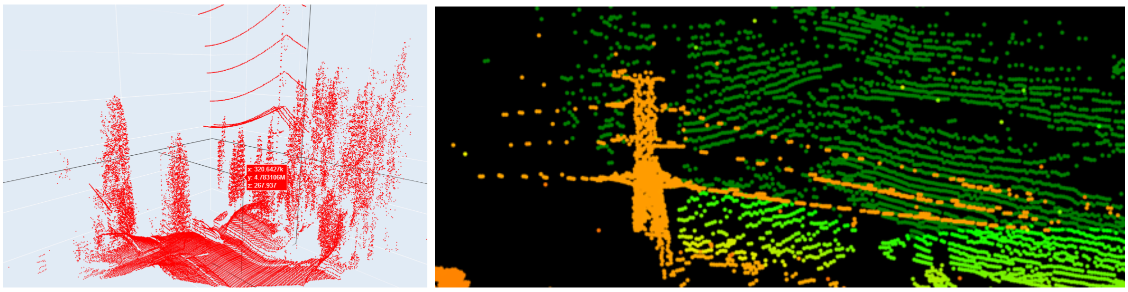


Fig. 5. example of Lidar point clouds (simulated on the left and real on the right)

The ODD is not merely a static document but a dynamic tool for continuous improvement. It quantitatively assesses the system's limits by benchmarking model performance against the volume and variety of available data used for training. This process of continuous validation highlights gaps in the AI's capabilities, thereby defining a clear roadmap for system improvements. Performance extensions can be achieved through successive new training cycles, where the dataset is specifically enriched to address the identified weaknesses.

Furthermore, there is a strong symbiotic link between the ODD and the AI model architecture itself. Given the wide diversity of obstacles and environments encountered during helicopter missions—ranging from detecting thin wires in bright daylight to classifying terrain features in snowy conditions—a single, monolithic AI model would not be sufficient. Such a model would struggle to perform optimally across all conditions, as the features required for one task can conflict with another. We therefore propose a modular AI architecture, potentially using a "mixture of experts" approach. In this framework, multiple specialized AI models are trained to excel at specific tasks or within specific environmental conditions defined by the ODD. For example, one model could be an expert in wire and pole detection, another specialized in vehicle classification, and a third optimized for performance in degraded visual environments. A high-level executive function would then intelligently select and fuse the outputs from the most relevant models in real-time based on the current operational context, ensuring that the most effective processing is always applied.

THE AI MODELS

Building on the modular concept, our proposed architecture uses several types of AI in a hierarchical structure to manage both the sensors and the perception task itself. A **first-layer AI model** could act as an intelligent "Sensor Manager." By analyzing the external conditions defined in the ODD (e.g., ambient light, precipitation, visibility), this model would dynamically assess the reliability of each sensor in the multispectral suite. For instance, in heavy fog, it would increase the weight given to radar data, while in clear conditions, it might prioritize inputs from the optronics suite for higher-fidelity classification.

The output of this optimized sensor stream would then be fed to a **second layer of AI models** dedicated to performing the core perception task of **Detection, Recognition, and Identification (DRI)**. These are the specialized "expert" models.

- **Detection:** The system first determines that an object of interest is present in the sensor data.
- **Recognition:** It then categorizes the object into a general class, such as "vertical structure," "vehicle," or "aircraft."
- **Identification:** Finally, it attempts to identify the specific type of object, for example, distinguishing a high-voltage transmission tower from a wind turbine or a telecommunications antenna.

The effectiveness of these DRI models is entirely dependent on the quality of their training. For example, to reliably identify wind turbines and antennas, the models must be trained on extensive datasets containing these objects. The following image shows the direct result, or **inference**, of an AI model trained specifically on such data, which was largely generated within a high-fidelity simulator. The model correctly processes the input and draws bounding boxes around the identified objects, demonstrating a critical capability for safe navigation in proximity to such structures:

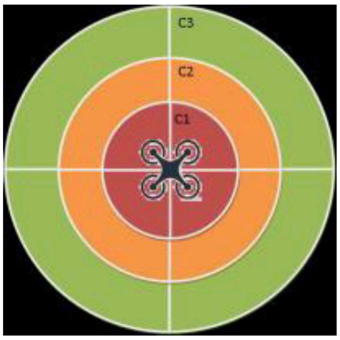
Fig. 6. example of windmills & poles detection and classification

Examples of AI use for SAA

1) Sensor choice according to the time before impact

In this context, the present text details the use of AI for the detection and classification of fixed and mobile obstacles. An aircraft equipped with a piloting system, a plurality of sensors, and a computer implementing an AI model enables this function.

Obstacle detection is achieved across three distinct spatial zones, arranged by proximity to the aircraft and correlated with varying Time Before Impact (TBI) thresholds. Each sensor array contributes to comprehensive coverage within at least one of these zones. Overlapping regions between zones ensure spatial continuity and facilitate robust true positive detection through multi-sensor corroboration.



		SENSE AND AVOID					CONNEXE TECHNICAL BRIKS		
Sensor	Nbr	Front	Rear	Left	Right	Up	Down (L/G Help)	Localization (SLAM)	Circle num
US	6 – 8								C1
IR	10 – 12								C1
LIDAR MULTI-POINTS	1 (Scan)								C1-C2
LIDAR UN POINT	1 (Altimeter)								C1-C2
RADAR P	1								C2-C3
RADAR A	1								C1-C3
Cam Mono	5-10		Low-cost						C1-C3
Cam Stereo	5-10		Low-cost						C2-C3

Fig. 7: Spatial detection zones versus Time Before Impact versus sensor choice allocation

The onboard computing system processes sensor data from detected obstacles to ascertain key attributes including position, velocity, trajectory, Time Before Impact (TBI), physical dimensions, and classification (e.g. static structure, avian risk, other aerial vehicles). This analytical capability is augmented through the fusion of data streams from disparate sensors or varied sensor modalities. The aggregate of this information serves as the input framework for a Fuzzy Logic model. Upon confirmation of a potential collision scenario (e.g. exceeding a predefined minimum separation distance or trajectory threshold), the system computes an optimal avoidance maneuver, which may generate a revised flight path (rerouting) or issue a direct command to modify aircraft state (e.g. adjustments of speed, acceleration, or load factor). These corrective actions are engineered to mitigate the collision risk while adhering to established aircraft operational envelopes, passenger comfort parameters, and payload integrity considerations. The integrated piloting system is then commanded to autonomously execute the determined avoidance sequence.

The system prioritizes early detection, especially in the outermost detection zone, enabling detailed analysis and facilitating smoother, optimized avoidance maneuvers. When an obstacle is identified in the mid-range zone with ample TBI, avoidance actions can be deferred, and the obstacle merely tracked. Conversely, for imminent threats (close proximity or minimal TBI), pre-programmed emergency maneuvers are instantly executed. Furthermore, detected obstacles are assigned a weighting based on their detection zone, range, characteristics (e.g., dimensions, mass, velocity, TBI), and the aircraft's capabilities.

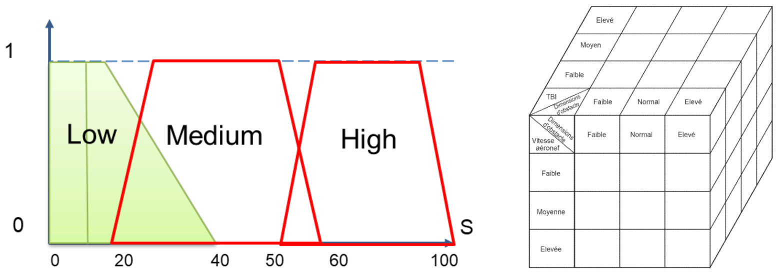


Fig. 8. Example of H/C speed (S) membership diagram and Parameter Weighting Rules cube

This weighting mechanism aids in prioritizing avoidance responses, particularly in multi-obstacle scenarios. Fuzzy logic and deep learning algorithms are employed to determine obstacle characteristics (fixed vs. mobile) and assign corresponding weightings.

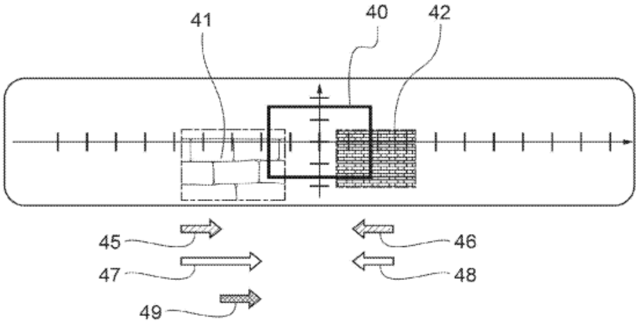


Fig.9. Example of HMI giving the relative multi obstacle scenario

The system can operate either fully onboard the aircraft or with partial remote computational support (e.g. a ground piloting station). Conceptually, the three detection spaces align with human brain functions: the outermost space with long-term strategic thinking (frontal cortex), the middle space with short-term perceptual reflection (visual/auditory cortex), and the innermost space with immediate, reflex-driven responses (amygdala).

This system can be used for small objects such as birds and drones

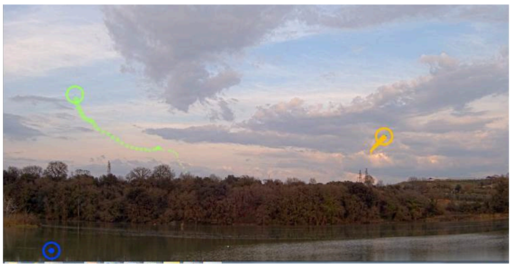


Fig. 10. AI model for birds and UAV detection

2) Example of AI for wire detection

Following the discussion on the detection and differentiation of general obstacles, including small flying objects like birds and drones, the AI-based SAA system extends its capabilities to specific threats. In this regard, another crucial AI application is presented: the development of an improved means for cable detection. This function, essential for low-altitude flight safety, is implemented by combining three types of AI, described below, thus offering a robust and nuanced approach to cable detection.

This function, for instance, leverages three distinct AI methodologies to improve wire obstacle detection and ultimately enhances flight safety. Specifically, deep learning is employed for the recognition and identification of pylons within environmental imagery captured by the detection system. This approach enables the system to robustly learn and identify various pylon shapes and families across diverse angles and distances. Neural networks, such as Convolutional Neural Networks (CNNs) or Transformers, are suitable architectures for this purpose.

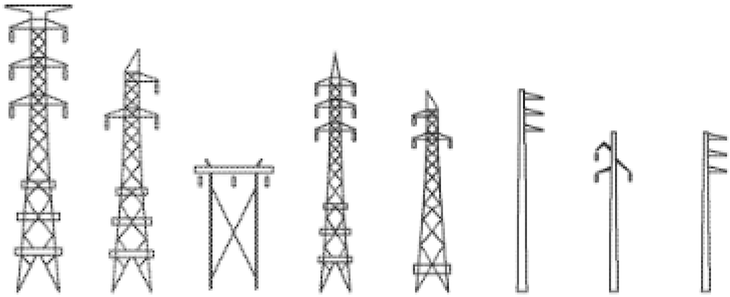


Fig. 11. Typology of pylones considered in Expert System

Additionally, a database stores pylon family characteristics and expert system rules. These rules, derived from pylon and cable design/installation principles, enable the characterization of cables potentially supported by a detected pylon, including inter-pylon distance, cable count/category, and curvature. This expert system facilitates the inference of cable presence and attributes, even when direct detection is challenging.

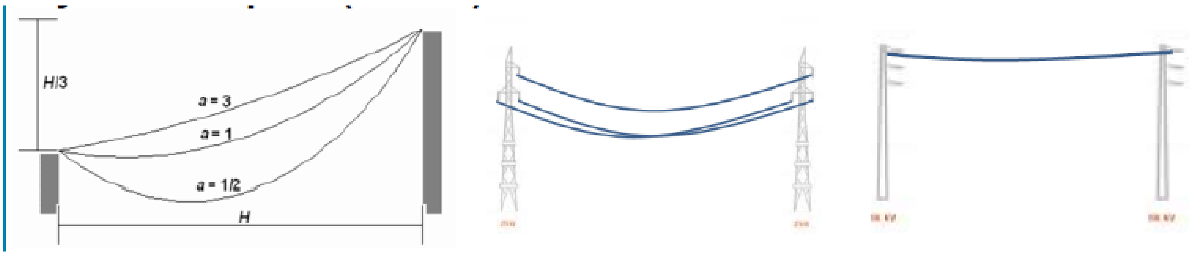


Fig. 12. Example with different numbers of cables and different cable curvatures

Furthermore, Fuzzy Logic is employed for deterministic and dynamic calculation of safety distances (prohibited zone in red, safe zone in green, and contingency zone in amber):

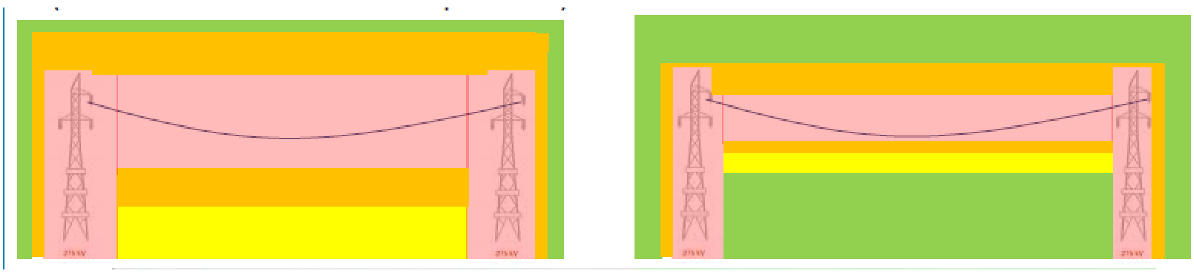


Fig. 13. Evolution of the no flight, safety margin and clear zone

These distances are continuously adjusted based on real-time flight criteria, including aircraft speed, obstacle distance, Time Before Impact (TBI), and the confidence level in pylon detection and identification. This approach enables a nuanced and adaptive definition of safety zones, offering greater flexibility than binary methods. A decision matrix can also complement fuzzy logic for complex criterion combinations, like on the following illustration:

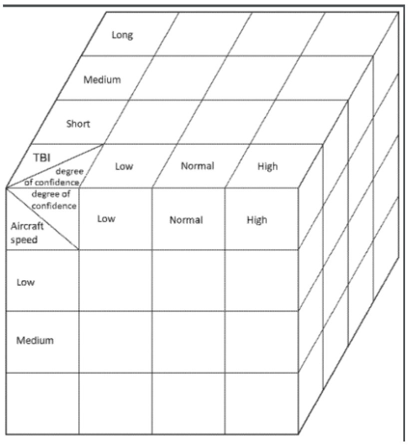


Fig. 14 Fuzzy Logic Weighing Rules Cube

The images below illustrate the implementation of this system on a drone equipped with a standard camera. The left image shows the video captured by the camera. The right image demonstrates the functionality of the three AI models, as the pylons are detected (marked by yellow segments), and high-risk collision zones are indicated by a color gradient:

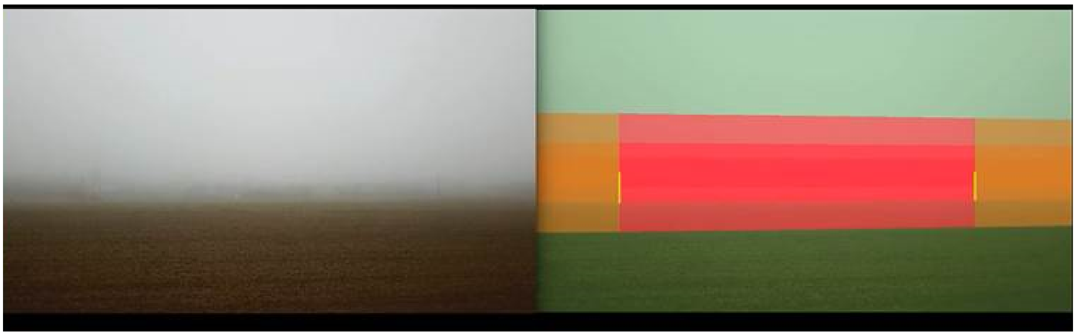


Fig. 15. Wire detection flight demonstration in a degraded environment (fog)

The illustrations below depict a drone flight over pylons. The model, leveraging data from the expert system, proposes a continuous high-risk zone both upstream and downstream of the pylons detected by the camera.

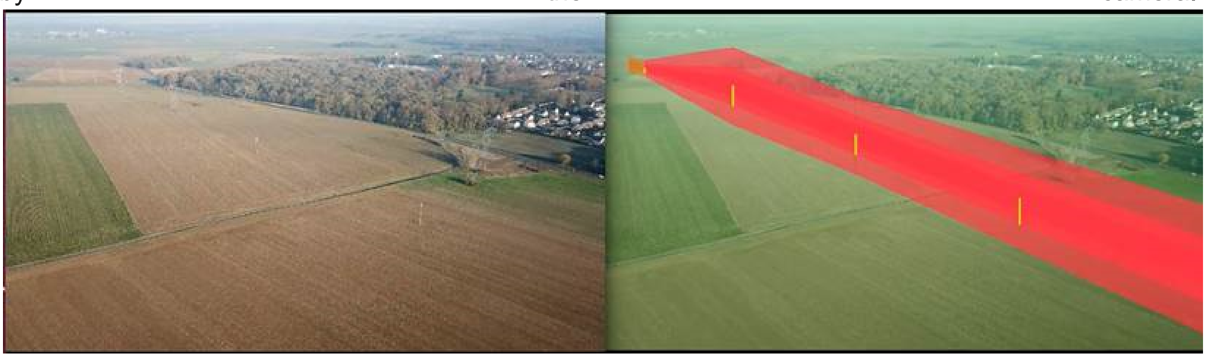


Fig. 16. Pylons and wire detection with expert system AI flight demonstration with non-degraded environment

Following the previous examples of detection in challenging environmental conditions like fog, we will now explore how to select the optimal sensor set and the appropriate AI model to enhance the system's performance.

3) Sensor set and detection AI model selection methodology

Beyond detecting and avoiding static obstacles and fixed infrastructure, the Sense and Avoid system further leverages AI to dynamically optimize its own sensor configuration and overall operational intelligence, a critical step towards comprehensive situational awareness in increasingly complex airspaces and multi-asset scenarios.

To summarize our AI applications, we can implement AI to select the most suitable sensor array based on specific environmental conditions. The aircraft, featuring diverse navigation sensors, employs an autonomous piloting system to select the optimal sensor combination according to current flight and environmental parameters, thereby ensuring precise navigation.

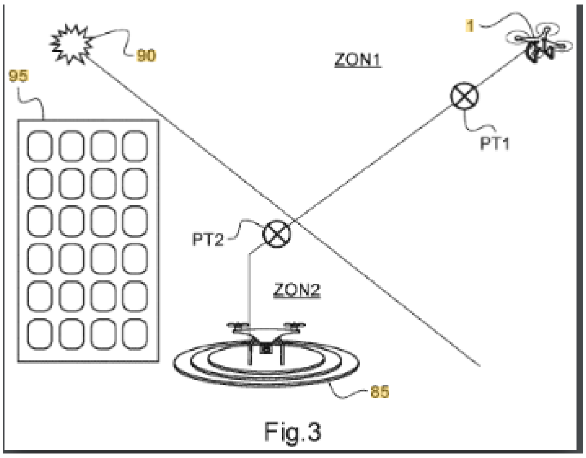


Fig. 17. Evolution of environment conditions during flight and landing phase

Initially, the system ascertains flight condition parameters, including luminance, illuminance (NVE), environmental contrast (NVC), distance to obstacles (NVD), and aircraft speed (NVV). These specific parameters are independent on the sensors' intrinsic image quality:

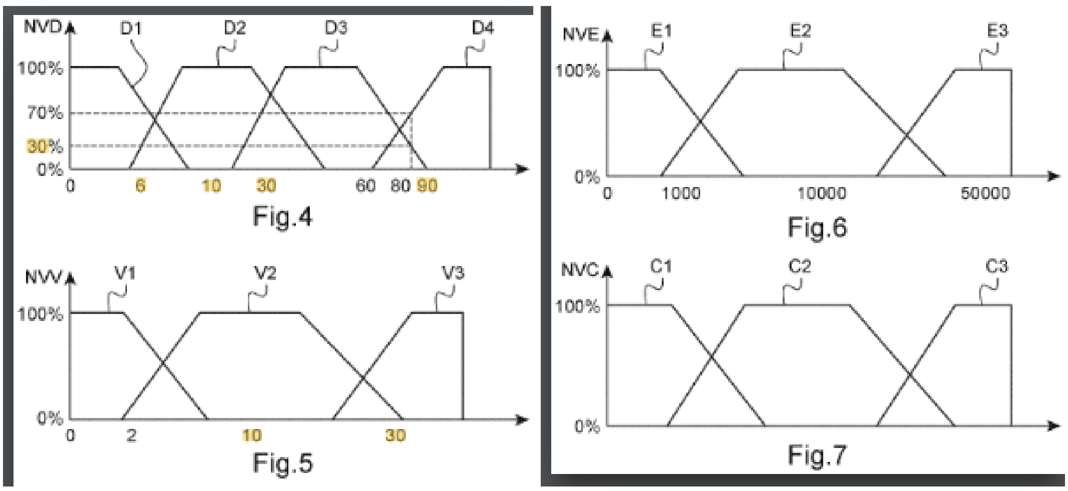


Fig. 18 Fuzzy Logic Membership diagram corresponding to environment conditions and flight parameters

An embedded fuzzy logic selection model is used to identify the most pertinent sensor configuration. For each flight condition parameter, a membership level across predefined categories (e.g., low, medium, high) is computed. Subsequently, a weighting is assigned to various rules, each rule correlating a specific sensor set with combinations of these categories. The sensor set exhibiting the highest weighting is then chosen.

Ultimately, the command controller generates flight control signals based on the data from the selected sensor set. This dynamic adaptation enables the aircraft to respond in real-time to evolving conditions, such as intense light or shadows, by deploying the most effective sensors for the prevailing situation (e.g., radar and or IR imaging in direct sunlight, infrared in darkness and visible imaging in best visual conditions).

Beyond sensor selection and fusion, the system can embed multiple AI models, dynamically chosen based on the sensor configuration and environment to ensure robust inference during flight. Furthermore, an "Executive Function" AI model acts as a master controller for the perception module. This deterministic model, potentially employing fuzzy logic, selects the appropriate Detection, Recognition, and Identification (DRI) "expert" model to be activated. It processes inputs such as mission type (e.g. low-level transit, hover), expected obstacle typology, and external conditions (e.g. "poor visibility," "over urban terrain"). Based on a predefined set of human-engineered rules, this executive model robustly handles inherent imprecision to deterministically select the most suitable combination of experts for the Sense and Avoid function at any given moment, thereby guaranteeing optimal system configuration for the immediate operational context:

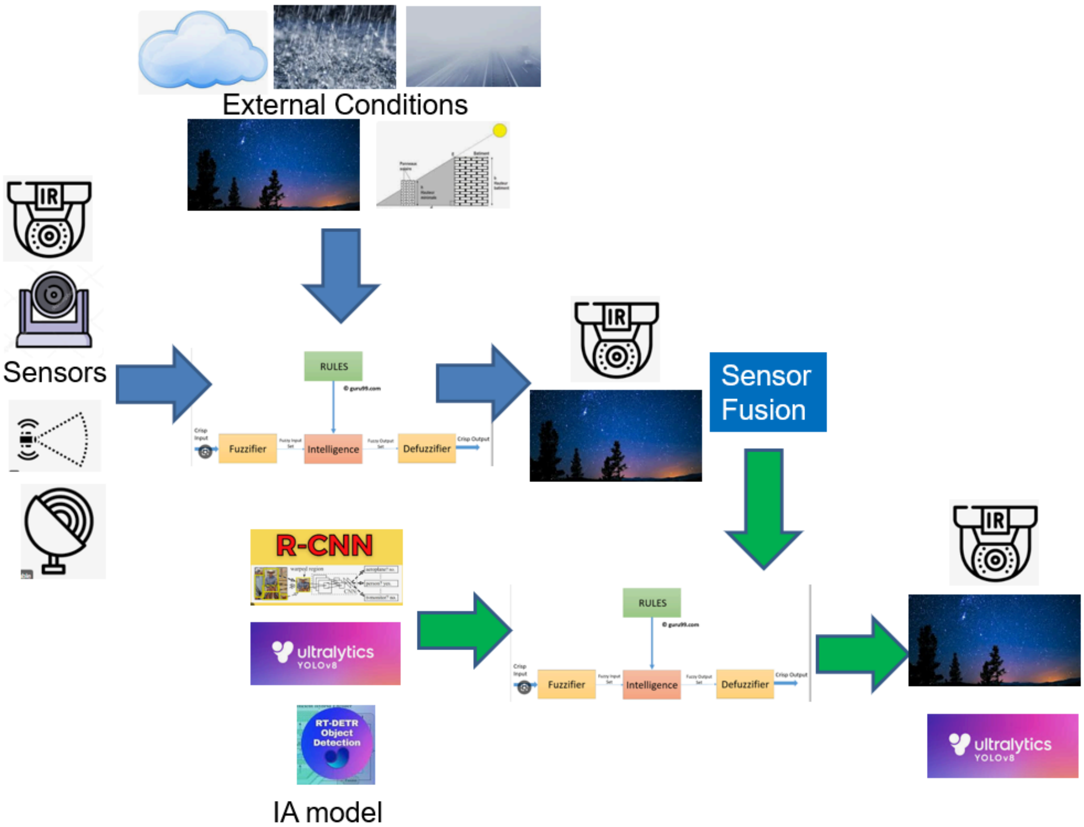


Fig. 19. Concept of IA to select the best sensor and the best associated AI model

As an illustration of tested sensors in the field of Radar, we have already demonstrated the potential contribution of a Radar from the automotive market to SAA function.

These demonstrations showed a capability for drone detection and tracking, as well as static obstacle detection:

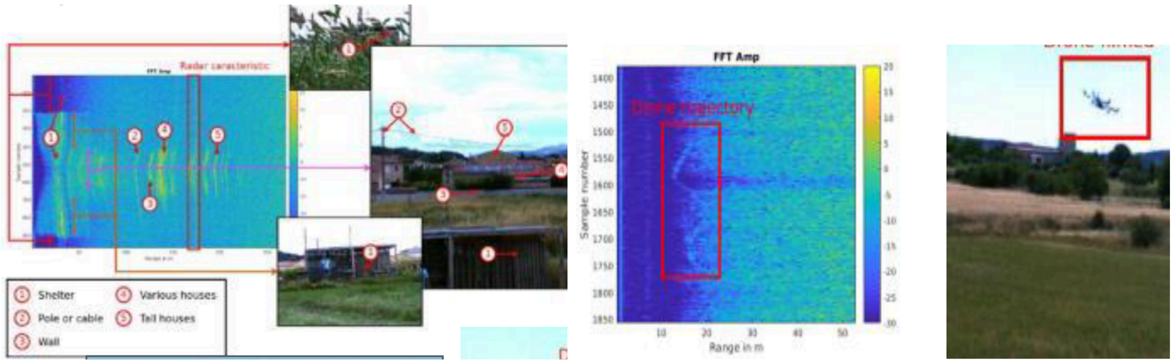


Fig. 20. Drone detection and tracking

CONCLUSION

In conclusion, while classical Sense and Avoid systems have laid a crucial foundation for aviation safety, our proposed approach represents a significant leap forward by integrating multi-modal sensor fusion and advanced AI. This enables a transition from reactive avoidance to proactive and predictive safety functions, vital for the next generation of autonomous aviation. By strategically combining diverse sensor technologies—such as optronics and radar—and leveraging AI for robust obstacle detection, including wires, and dynamic sensor/model selection based on environmental conditions, our system ensures comprehensive, all-weather situational awareness. This modular and adaptable architecture, with its executive AI function, is designed to enhance piloting precision and efficiency, ultimately paving the way for safer and more autonomous flight operations across both civilian and military domains, while meticulously considering human-machine interaction and regulatory compliance.

Naturally, the systems described in this paper will need to collaborate with the already existing collaborative traffic management systems, like ADS-B and ACAS/TCAS, and the recent ACAS-Xu and ACAS-Xr.

REFERENCES

1. H-M Huang; *Autonomy Levels for Unmanned Systems (ALFUS) Framework*; NIST Special Publication 1011-II-1.0, 2007
2. *EASA Concept Paper: guidance for Level 1 & 2 machine learning applications*; Feb 2023
3. Y. Wang, X-Y. Zhang, C-L. Liu, Z. Zhang; *Emergence of Machine Language: Towards Symbolic Intelligence with Neural Networks*; January 2022
4. Patent FR3110999B1, Lionel THOMASSEY, publication n° 3 110 999, Method and system for detection and avoidance of obstacles with several detection spaces for aircraft
5. Patent EP3798675B1, Lionel THOMASSEY, Method and system for detecting wired obstacles for aircraft
6. Patent FR3118000A1, Lionel THOMASSEY, method of piloting an aircraft having a plurality of dissimilar navigation sensors and an aircraft

GLOSSARY

4D	Dull, Dirty, Difficult, Dangerous
AI	Artificial Intelligence

ADSB	Automatic Dependent Surveillance–Broadcast
ALFUS	Autonomy Levels For Unmanned Systems
CONOPS	CONcept of OPerationS
CNN	Convolutional Neural Networks
DAA	Detect And Avoid
DRI	Detection Recognition Identification
DVE	Degraded Visual Environment
EASA	European Union Aviation Safety Agency
EC	Environment Complexity
EUDAAS	EUropean Detect And Avoid Solution
HEMS	Helicopter Emergency Medical Services
HMI	Human Machine Interface
LOA	Level Of Autonomy
LIDAR	Light Detection and Ranging
MC	Mission Complexity
MUM-T	Manned Unmanned Teaming
NASA	National Aeronautics and Space Administration
NOE	Nap of the Earth
ODD	Operational Design Domain
RPAS	Remotely Piloted Aircraft Systems
SAA	Sense And Avoid
SAR	Search and Rescue
SWaP-C	Size, Weight and Power - Cost
TBI	Time Before Impact
TCAS	Traffic alert and Collision Avoidance System
UAM	Urban Air Mobility