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MACHINE LEARNING BASED VISUAL NAVIGATION SYSTEM ARCHITECTURE FOR AAM OPERATIONS WITH A DISCUSSION ON ITS CERTIFIABILITY

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Abstract

Advanced Air Mobility (AAM) is expected to revolutionize the future of general transportation expanding the conventional notion of air traffic to include several services carried out by autonomous aerial platforms. However, the significant challenges associated with such complex scenarios require the introduction of sophisticated technologies able to deliver the resilience, robustness, and accuracy needed to achieve safe, autonomous operations [39]. In this context, solutions based on Artificial Intelligence (AI), able to overcome some limitations found in traditional approaches, are becoming a major opportunity for the aviation industry, but, at the same time, a significant challenge with respect to the certification standards.

With the focal point on further proposing a certifiable architecture for AI-enhanced vision navigation in AAM operations, this paper first, summarizes the current technologies and fusion methods applied to date to navigation purposes, to later address the certification problem. Regarding certification, it explores three specific points: 1) traditional certification procedures; 2) current status of AI homologation recommendations; and 3) other certification factors to be considered for future discussion.

Introduction

Urban Air Mobility (UAM) pretends to define safe and efficient air traffic operations performed by highly automated aircraft operating at lower altitudes within urban areas. Likewise, Advanced Air Mobility (AAM) builds upon the UAM concept by incorporating operations out of urban environments, such as: intercity passenger transportation, cargo delivery and/or other public or private services. In this context, several parallel efforts are focusing on defining the Concept of Operations (ConOps) for the initial phases of UAM and AAM. These studies suggest different perspectives of the high-level operational procedures, but all agree that safety must be the key principle. However, significant challenges arise when requiring technologies to deliver the strict performance needed to substitute the onboard pilot. Specifically, regarding navigation, operational procedures state that AAM vehicles shall estimate their own position accurately during all flight phases avoiding Single Point of Failure (SPOF) systems.

Due to the limitations associated with GNSS-based navigation systems, present commercial Position, Navigation and Timing (PNT) solutions start offering alternatives completely independent to GNSS techniques, typically based on pseudolites and vision technologies. Although pseudolites approaches provide accurate, reduced cost and easy integration solutions, they are susceptible to the same signal interferences as GNSS-based solutions. Conversely, visual-based localization techniques, an active research area, are gaining ground because of some of their advantages such as their immunity to external interferences and their adaptability to all types of platforms while satisfying payload size, weight, and power (SWaP) requirements.

However, although visual-based solutions present promising results, they are still not mature enough to provide the resilience required for AAM operations. Thus, to overcome this limitation, two different strategies are addressing the problem. Firstly, combinations of dissimilar sensors operating at different wavelengths focus on compensating the limitations of each technology and expand the operational range of the overall solution. Secondly, traditional fusion methodologies are being replaced by Machine Learning (ML) techniques, which have demonstrated that are able to overcome some of the deficiencies present in traditional methods.

Therefore, ML techniques are becoming a major opportunity for the aviation sector but also a significant challenge due to the strict certification procedures implemented in this industry. Accordingly,

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some of the most important civil aviation authorities (CAAs), such as the Federal Aviation Administration (FAA) and its counterpart in Europe, the European Union Aviation Safety Agency (EASA), are currently focused on establishing the basis of certification procedures related to AI technologies for aerospace systems. Besides, in recent years, different technical reports have been published addressing problematic aspects of ML homologation, such as verification, validation, traceability, or coverage. However, due to the strict certification protocols, all reports drastically limit the considered ML applications to a reduced group which meets rigorous conditions, leaving apart a huge number of great-potential methodologies that could be key for achieving safe autonomous, aerial operations.

Within this framework, and with the final goal of designing a certifiable architecture for an enhanced vision navigation system based on AI, this work encompasses the following points. It begins by summarizing the benefits of enhanced, visual navigation technologies and ML fusion methods in comparison to historical solutions. Then, the certification discussion starts by introducing the key aspects of the traditional aviation homologation process in order to increase the awareness of them. In continuation, the circulating considerations and recommendations related to AI-based solutions are analyzed. Finally, some novel ideas that could be considered in order to open the certification doors to all categories of ML applications are brought up.

Navigation technologies

Even as technology advances, GNSS still remains an integral part of current navigation systems. GNSS-based technology, empowered by its augmentation techniques such as GBAS, RTK or DGNSS, provides accurate PNT. However, these solutions are vulnerable to intended or unintended radio interference, as well as to multipath errors. Consequently, pushed by the demanding performance required in AAM operations, there is at present a huge effort focused on developing navigation solutions able to overcome these deficiencies. One of the most considered technologies corresponds to pseudolites, which provide a ground-based GPS alternative. Some others rely on VOR/DME technologies. Nevertheless, both of them are also susceptible to signal interference, and they depend upon external systems for acquiring the necessary information for computing the aircraft position.

On the other hand, visual-based localization techniques have long been an active research area since they present several advantages such as relying on exteroceptive sensors for sensing the surroundings, which make them immune to external interferences while typically satisfying payload size, weight, and power (SWaP) requirements, being able to be adapted to all types of aerial platforms.

However, while it is true that only a visual camera does not span the whole spectrum of situations expected in AAM, a multi-source localization approach, avoiding, also, Single Point of Failure (SPoF) systems, could be the proper solution. The idea builds upon incorporating complementary and redundant sources of information not only to overcome individual sensor weaknesses, but also to expand the operational spectrum and reliability of the final approach. Thus, for instance, fusing vision and infrared cameras allows to achieve robustness to illumination effects, expanding the operational range to night-time and poor weather conditions, introducing stereo configuration, LIDAR or altimeters enables depth computation, while accuracy can be improved by adding Inertial Measurement Units (IMUs).

To this end, a deep study about the exploitable technologies for navigation purposes has been performed. Table 1 gathers the main strengths and weaknesses of every one of them.

Table 1. Benefits and drawbacks of the different technologies used for navigation purposes

Technology	Advantages	Disadvantages
GNSS	- Absolute Positioning - Easy integration and low cost - High accuracy (with augmentation techniques) - All weather and all light conditions	- Not self-contained - Radio interferences - Multipath error - Susceptible to external attacks - Low acquisition rate
Visual camera	- Self-contained - Easy integration and low cost - Immune to external disturbances - Simple calibration - Navigation accuracy between 0.1-2%	- Relative position - Scale uncertainty - Texture / light dependency - High computational cost - Blur images in high-dynamical systems
Stereo cameras	- Self-contained - Depth information available - Immune to external disturbances - Accuracy around 0.1 and 2%	- Relative position - Precise calibration required - Complex synchronization - High computational cost - Texture / light dependency - Blur images in high-dynamical systems
Inertial systems (Low SWaP)	- Self-contained - Robust in high-dynamical systems - High acquisition rate - Easy integration and low cost - All weather and all light conditions - Immune to external disturbances	- Unsuitable for positioning - Drift over time - Stationary error
Infrared camera	- Self-contained - All weather and all light conditions - Easy integration and medium cost - Immune to external attacks	- Relative position - Scale uncertainty - Lack of features - High computational cost
Near-Infrared camera	- Self-contained - All weather and all light conditions - Easy integration and medium cost - Immune to external attacks - Very sensitive to natural elements	- Relative position - Scale uncertainty - Lack of features - High computational cost - Light dependency
Laser range (altimeter)	- Self-contained - Accurate depth position - Easy integration and low cost - All weather and all light conditions	- Only measures the distance to a point - Accuracy depends on the target material - Stationary error
LIDAR	- Self-contained - High accuracy - All weather and all light conditions - Accurate depth position	- Expensive and complex integration - Power consuming and heavy - High computational cost - Relative position

	- Full environment understanding	- Range depends on atmospheric conditions
VOR / DME	- Absolute Positioning - All weather and all light conditions - Large number of stations available - Easy integration and low cost	- Not self-contained. - Requires recurrent ground stations - Accuracy around 200 meters and 0.35º - Ground stations require periodic calibrations - Limited to line-of-sight - Availability depends on current traffic
Pseudolites	- Centimeter accuracy - Absolute positioning - Easy integration and low cost - Same GNSS receiver compatible - Works with GNSS or independently	- Not self-contained - Require recurrent ground stations - Interference and multipath problems - Susceptible to external attacks - Complex time synchronization - Low acquisition rate
Low Earth Orbit (LEO) satellites	- High accuracy - All weather and all light conditions - More resistant to interference - Easy integration	- Not self-contained - Orbit determination uncertainties - Reduced coverage (more satellites required) - Private infrastructure
Event camera	- Self-contained - Very high acquisition rate - High pixel bandwidth - Low power consumption	- Acquisition software to be developed - Expensive - Relative position - High computational cost - Light dependency
Signals of Opportunity (SoO)	- Incredible signal diversity - High power signals - No additional infrastructure required	- Not self-contained - Availability varies by location - Transmitter locations must be known - Requires complex wideband antenna - Multipath and non line-of-sight problems - Not optimized for positioning

On this basis, one of the decisive concerns when designing a positioning solution corresponds to the selection of the involved sources of information and its optimal fusion architecture.

Traditional vs AI-based fusion methods

To date, countless different strategies have been applied for position estimation. While it is true that some of them involve a unique sensor, the latest trends advocate for considering measurements from different devices, due to the reasons mentioned before. Therefore, sensor fusion has become a vital process in complex and critical applications such as aircraft positioning [1].

Sensor fusion refers to techniques focused on combining data (processed or unprocessed) from different sources of information to produce a final solution composed by the combination of all available data. Fusion algorithms consider the advantages and disadvantages of every technology as well as tackle the redundancies and complementarities of the whole architecture. Thus, the final result corresponds to an improved and more trustworthy solution while increasing the resilience and expanding the operational range of the application.

Traditional localization approaches, based on physical models or geometry theory, mainly apply statistical and probabilistic fusion methods [6][7][8][9]. Although they are able to achieve, in

some cases, satisfactory accuracy, the final approaches do not procure enough reliability to operate in real AAM scenarios. Some of the limitations commonly found in these applications are:

- Inability to estimate and maintain the absolute scale of the scene.
- High sensitivity to external environmental conditions, such as light intensity, poor weather situations such as fog, snow or rain.
- High sensitivity to high dynamical systems resulting in blurry images
- Night vision difficulties
- Problems when handling low texture images
- Inability to operate in dynamic environments, where surrounding objects are not static.
- Lack of adaptability to specific environments

Thus, with the main focus on solving these and other deficiencies and thrusted by new technological advances for parallel processing, and the enormous amounts of data easily available, ML techniques are progressively replacing traditional fusion methodologies.

Depending on how ML techniques are applied, it is possible to differentiate two groups of approaches:

- End-to-end: entirely composed by ML techniques. They are an alternative to separated methods for detection, matching and/or estimation, since they perform all of the steps at once [10][11][12][13].

- Hybrid: integrates classical geometric models with a ML framework. Thus, they replace parts of a geometric model with ML techniques. For instance, proposed works are already focused on extracting visual features [20], estimating and maintaining depth using a monocular architecture [19], real time data fusion [14][15][16] or loop closure in SLAM applications [17][18].

Besides, another possible classification is made according to how the learning process is performed:

- Supervised: learn by using labeled data. These applications map the inputs to the known results to find the relation between both. The final goal is to apply the learned patterns to unknown data to predict discrete (classification) or continuous (regression) values. They require supervision during the learning process by matching the predictions.
- Unsupervised: learn by using unlabeled data and without any guidance during the learning process. Similarly to supervised learning, their main aim is to explore the underlying patterns and predict outputs, but without any previous knowledge. To this end, they explore the association and relationships between input values to group them, that is, they perform association and clustering tasks.
- Reinforcement Learning (RL): learn by interacting with the environment on their own, following a trial and error procedure. During the learning process, without any supervision, these applications go through different discrete steps. At every step, the applications get a reward based on whether the previous decision was correct or not.

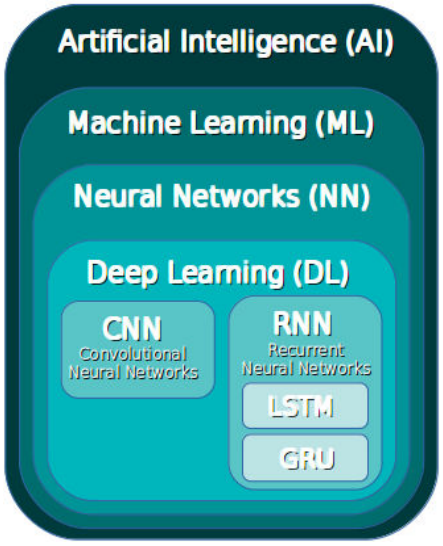

Figure 1. Taxonomy of AI

Finally, when talking about ML-based approaches, we refer to methods able to explore and learn relationships between different sources of information. However, ML covers a huge number of different methodologies that can be applied for aircraft navigation. Figure 1 shows the taxonomy of AI, contextualizing the most important ML techniques inside this field.

While AI refers to the ability to imitate intelligent human behavior, ML specifically includes the capacity to automatically learn and improve from the experience. On their side, Neural Networks (NNs) refers to an interconnected group of artificial neurons,

mimicking the human brain, able to classify input information according to a mathematical function based on weights and biases which are learned during the training process. Although NNs are capable of uncovering simple underlying patterns, Deep Learning (DL) is preferred when handling challenging hidden relations. This is because DL comprises multiple NNs layers, making them more complex, but increasing their capacity to model highly non-linear associations from a large amount of data. Finally, Convolutional Neural Networks (CNNs) correspond to NNs adapted for analyzing and identifying visual data from input images while Recurrent Neural Networks (RNNs) are a type of network modified for analyzing temporal dynamic behavior.

At present, the most promising architecture for aircraft localization and navigation approaches based on ML techniques corresponds to CNNs used to estimate the spatial features from one or several cameras, and a Long-Short Term Memory (LSTM) architecture applied to estimate the temporal variation of these features from which the final pose may be estimated [5].

Generally, ML-approaches permit learned models to be resilient and adaptive to environmental changes. Some of the key aspects that learning approaches offer over traditional methods are:

- More robust to calibration and timing errors.
- Extract high-level features, which, in contrast to hand-crafted feature extractors, make them more robust to featureless areas, changing light conditions and/or blurring.
- Model the motion dynamics, handling highly non-linear systems.
- Handle optimization problems related to data association (matching, map optimization).
- Allow to combine multi-sensor information providing a final enhanced estimation.
- No necessity of system's prior knowledge

However, despite the benefits shown by ML methods, some considerations must be kept in mind:

- They require large amounts of data correctly labeled for training purposes.
- ML applications are considered as black-box models since their architecture does not allow an easy human understanding.

AI certification discussion

Since its inception, one of the pillars on which civil aviation has been founded corresponds to safety. To this end, big efforts have been put into setting the rules and procedures that ensure safety air operations. On the other hand, civil aviation corresponds to a worldwide marketplace, so it is expected that the CAAs are harmonized in the demanded requirements. Specifically, regarding the software in airborne systems, the current applicable guideline around the world is the standard DO-178C, which is focused on assuring that software developed for avionics systems is reliable and safe to be used in flight.

However, although DO-178C corresponds to an updated version approved in 2013, it does not make any allowance for adaptive approaches, putting aside all applications based on AI. Thus, in order to cover this gap and allow taking advantage of the great potential of AI-based applications in airborne systems, different CAAs are currently working on the implementation and certification processes related to AI technologies for aerospace systems. Moreover, in parallel, numerous researches address specific problematic aspects of AI certification, such as verification, validation, traceability or coverage, trying to find solutions to some of these points, which could ease and accelerate the certification course.

Traditional aviation industry standards

At the present time, the development of aviation systems is designated by the compliance of three fundamental standards, addressing each of them different aspects of aircraft certification: DO-178C (software), DO-254 (hardware), and ARP4754A (high-level system integration). Thus, DO-178C, titled Software Considerations in Airborne Systems and Equipment Certification, describes the software planning process, software development process, and the verification activities for delivering high-quality avionic software. Therefore, standard DO-178C is the principal document used by applicants to develop all commercial software-based aerospace systems, as well as by the CAAs to validate them.

DO-178C was published by the Radio Technical Commission for Aeronautics (RTCA) and the European Organization for Civil Aviation Equipment (EUROCAE) and approved by the FAA in 2013. The standard corresponds to an updated version of the document DO-178B, released in 1992, upgraded to

include the progress in software technology during these two decades. Besides, DO-178C is accompanied by four technology supplements focused on different aspects which require detailed attention: tool qualification (DO-330), model-based development and verification (DO-331), object-oriented technology (DO-332), and formal methods (DO-333).

DO-178C is based on a framework for defining Development Assurance Levels (DAL). It defines five different levels, from A to E related to the gravity of a software failure. Thus, level A means ”Catastrophic” condition while E refers to ”No effect on safety”. The requirements to be covered for compliance depends on the specific level. Thus, applications categorized in level A must meet all safety requirements, while lower risk applications are less stringent, covering a decreasing number of requisites according to each specific level.

In order to assure software reliability, DO-178C demands the following key aspects to be demonstrated: absence of errors, coverage of all specific requirements based on the criticality level and bidirectional traceability between requirements, code and tests. Regarding coverage, DO-178C identifies two types of coverage:

- Requirements-based coverage: focused on demonstrating that all requirements can be validated through the proposed test cases.
- Structural coverage: refers to the necessity that the proposed test cases go through all code structure, ensuring the absence of ambiguous, or unnecessary code.

On the other hand, with respect to traceability, two-way connections must be evidenced between the requirements, source code and test cases. Thus, every specific test case must be linked to the requirement/s to be validated going through the portion of code that implements the functionality and vice versa. This step further guarantees the absence of orphan or dead code which cannot be traceable.

AI-based certification guidelines

In order to move forward towards the certification of ML solutions, three main difficulties inherent to the ML algorithms must be addressed:

- **Generalization problem**: since the behavior of every ML model builds up based on the data used during the training process, the main challenge regarding AI/ML certificability sits on the impossibility to predict the conduct of the application when facing situations out of the training range.
- **Non-deterministic behavior**: traditional software certification procedures focus on demonstrating the absence of unexpected behavior during the entire operation. To date, unexpected behavior derived from specific identifiable elements such as concurrency bugs, inadequate control conditions or unconsidered situations. So, once discovered, they can be mended. However, the behavior of an ML model is determined by a set of parameters learned during the training phase. Moreover, different learning methodologies (unsupervised, supervised or reinforcement learning) and several learning algorithms can be applied. Finally, the system can be pre-trained, using fixed weights during operation, or rely on online learning, adjusting the weights during the operation.
- **Requirements traceability and coverage**: As pointed out in the previous section, standard DO-178C demands bidirectional traceability between the requirements, code structure and test cases and full coverage evidence. In traditional applications, this is possible since the code is easily interpretable, but in the case of ML applications, the direct traceability and coverage is not feasible.

To overcome these obstacles, several researchers are focusing on solving these problems with the final purpose of finally enabling AI certifiability. In this line, [24] is focused on uncovering complex AI models to human users in a highly systematic, interpretable, and understandable manner, named as Explainable AI (XAI). [25] identifies the challenges and techniques to address the issues posed by learning-enabled components. [23] analyzes the design, requirements and test objectives related to ML-based low criticality airborne applications. Finally, [26] corresponds to a White Paper about Machine Learning in Certified Systems, which was the result of an international research program on Dependable and Explainable Learning.

On the other hand, different CAAs are currently working in the same direction, publishing diverse development guidelines which will facilitate the

further certification of the solutions designed following the recommended methodologies.

FAA & NASA

In the framework of the NextGen program, the FAA is working on identifying new opportunities to improve the efficiency and effectiveness of air traffic management operations. Activities ongoing include engineering to support the potential use of AI/ML to help National Airspace System (NAS) controllers.

Certification processes are being analyzed to assess FAA Artificial Intelligence system software assurance and check-out requirements to map out where current certification processes are adequate and where gaps exist as current certification standards for the aviation industry were developed before Machine Learning popularization without taking specifics of ML technology into account. Also, Adaptive Systems, widely used in Aviation applications, have been analyzed in detail by the FAA and NASA in regards to Neural Networks and deep learning implementations that aim to be certified.

The FAA checked the applicability of existing software assurance procedures, especially the DO-178C, with its supplements. Determining what the design assurance requirements should be for software aspects of those systems was the main focus of the Verification of Adaptive Systems tasks.

The outcome is clear, there are some fundamental incompatibilities between traditional design assurance approaches and certain aspects of ML-based systems. Specifically, it is still necessary to determine whether additional validation and verification (V&V) methods and activities or system-level constraints are needed to meet the DO-178C objectives.

More recently, NASA has put the focus into analyzing the certification of Low Criticality Airborne Applications in terms of traceability, coverage, and ML model verification issues. To mitigate these issues, NASA has proposed the basis of an ML development workflow, limiting the scope to non-adaptive, supervised learning systems with a specific breakdown between system and software/hardware artifacts inspired by the model-based design approach.

Finally, NASA has defined how the applicability of DO-178C, DO-331, DO-254, and ARP-4754 can be achieved for Low criticality Airborne ML Systems (Level D) using standard activities and methods.

EASA

Although there is no formal regulatory framework for AI in Europe, the European Union Aviation Safety Agency (EASA) has a clear roadmap to allow certification of ML/AI applications.

EASA identifies three general levels of AI starting with assisting functions (Level 1 AI), then making a step towards more human-machine collaboration (Level 2 AI) and at Machine autonomous behavior (Level 3 AI). The applicability of these guidelines is limited as follows:

- Covering Level 1 AI applications, but not covering Level 2 and 3 AI applications; ”No Safety Effect”,
- Covering supervised learning, but not other types of learning such as unsupervised or reinforcement learning;
- Covering offline learning processes where the model is ‘frozen’ at the time of approval, but not adaptive or online learning processes are approved.

As introduced in the EASA Concept Paper (EASA, 2021), AI/ML certification will be focused on three objectives which require further research:

- Guarantees on ‘ML model generalization’
- Guarantees on ‘Data completeness and representativeness’
- Guarantees on model robustness

In order to anticipate future guidance and requirements for safety-related machine learning application, the agency has released the concept paper: First usable guidance for Level 1 machine learning applications (EASA, 2021), combining the European Commission Ethical Guidelines with the EASA trustworthy AI building blocks that are considered essential for enabling the readiness of AI/ML in aviation.

It covers Level 1 applications; 1A-Human Argumentation, 1B-Human cognitive assistance in decision and action selection, shifting the paradigm from coding based applications to learning based applications. A description of Learning assurance, AI explainability and AI Safety risk mitigation building blocks is provided with especial emphasis in the W-shaped learning assurance process that supersedes the non-AI/ML component V-cycle process.

According to the Agency Roadmap the first AI/ML applications will be approved by 2025, by 2026 the

final framework and guidance for Level1 and Level2 will be in place and finally by 2028 the guidance for Level 3 applications will be ready being all enablers for single pilot and fully autonomous operations.

Proposed ML certification considerations

This paper introduces the following ideas to be considered when designing AI-based approaches, expecting to pave the way for their certifiability.

Algorithm redundancy

Redundancy has constituted a fundamental pillar of high reliability engineering over the latter decades. The objective of redundancy is to achieve fault tolerant systems, increasing, thus, their reliability by introducing duplicate elements. Moreover, redundancy not only enlarges the system reliability, but it also enables designers to quantitatively demonstrate it [31]. Three important concepts are associated to the redundancy applicability:

- **Independence**: one problem arises when the redundancy is introduced in a system by just duplicating existing elements since identical elements will likely fail under similar circumstances. To avoid this issue, the concept of dissimilarity or diversity design was introduced. The idea is based on the premise that introducing redundant but different elements, i.e. components performing the same tasks but based on different technologies or principles, will ensure failures in different ways and at different times [31].
- **Component redundancy vs partitioned redundancy**: redundancy can also be applied in a system at different levels. Component level means that the whole component is duplicated, while partitioned redundancy implies lower level duplicity. Both methodologies require similar resources, but partitioned redundancy has a significant reliability advantage, particularly if longer intervals are involved [32].

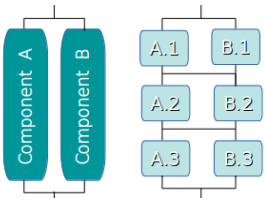

Figure 2. Component vs partitioned redundancy

- **Number of redundant elements**: dual redundancy allows to detect an anomaly, but usually more information is required to identify the corrupted element. Using three or more elements enables both, detect the fault and identify the source element.

Similarly to traditional safety-critical systems, redundancy could be applied in AI-applications in order to increment the reliability of the final solution. As Figure 3 shows, it could be implemented applying three different approaches:

1. Same AI architecture, but different datasets for training purposes.
2. Different AI architecture, but using the same training dataset.
3. Different AI architecture and different training datasets.

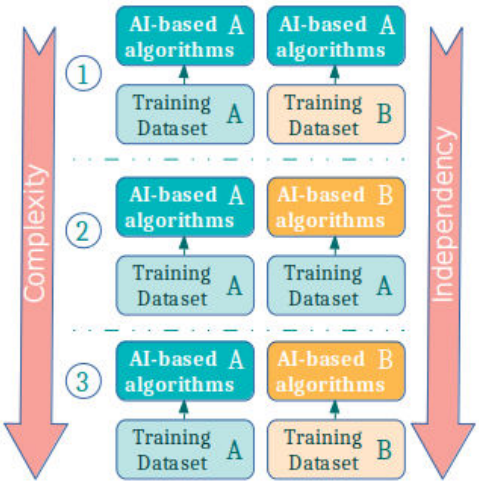

Figure 3. AI redundancy approaches

AI explainability (XAI)

As mentioned before, one of the concerns regarding ML applications is that they are considered as black-box systems. This impossibility to human understanding, makes them difficult to trust and, then, difficult to certify. XAI works on achieving AI systems transparency, enabling users to logically decompose and understand the system's result. "*With Interpretable AI, predictions can be logically justified, errors can be traced to their source in logical fashion, and a level of confidence in outcomes can be ascertained*" [34].

Thus, paying attention to interpretable AI when designing a new AI application could open the door to

solve the traceability and non-deterministic problems, easing their future homologation. Several works including [24] [30] [35] present recent developments and applications in this field.

ML/AI uncertainty

Similarly to XAI, there exist other emerging fields of study that aim to clarify additional aspects of AI/ML applications. In this direction, uncertainty quantification is gaining, also, a major significance since the importance of the output uncertainty when determining the confidence of a system. Currently, several researchers are putting a big effort on the challenge of developing accurate and formal uncertainty quantification tools enhancing the confidence and trustworthiness of AI/ML applications [36][37]. Considering this field of study by software developers could be a good practice to smooth their certification path.

Run-Time Assurance (RTA)

RTA architecture is defined in the standard F3269-17 [28] as "*a system of pedigreed components that implements real-time monitoring, prediction, and fail-safe recovery mechanisms that bounds the flight behavior of a non-pedigreed complex function to ensure the safety of a UAS*". Traditionally, RTA architectures have been applied to complex and/or experimental functions that cannot be fully tested. Standard F3269-17 provides directions to software developers regarding how to use RTA to restrict complex functions to ensure a reasonable level of safety. For its part, [27], a collaboration of the FAA and NASA, leverages it for providing safe operations of highly autonomous aircrafts.

Likewise, RTA mechanisms could be applied to ML-based applications to monitor, regulate and ensure the correct operation of ML models during their entire operation, but especially in the course of unknown scenarios. Applying this methodology and taking advantage of the previous knowledge of the system (flight dynamics, sensor performance, etc), it could be possible to bound the ML outputs while predicting anomalous operation of the ML algorithms. Thus, the generalization and non-deterministic behavior problems could be tackled directly. In this line, [29] presents a RTA architecture based on a NN aircraft taxiing application showing how RTA could be used to ensure safe operation.

Simulation tool to address Generalization problem

Supplement DO-330 (tool qualification), referred previously, establishes the directions on how to use external software tools, which can be applied to develop, assess or validate the main program, to gain certification credit. For that purpose, the tool qualification process focuses on ensuring the tool's trustworthiness. Moreover, bidirectional traceability between the requirements and the code, as well as an explanation on how the tool will be applied within the main program life cycle is also demanded [22].

Following these guidelines, a simulation tool could be developed based on traditional deterministic methods to diagnose and validate the AI-based application, especially in situations out of the training range. This simulation tool, designed according to the certification processes described in DO-178C, could be used to analyze the results of the ML-based algorithms not only using synthetic data (generated artificially), but also applying real data gathered from authentic flight operations. The use of such a tool would directly address the generalization problem while increasing the application's confidence and intelligibility, thus, raising the certification options.

Product Service History (PSH)

PSH corresponds to another strategy to acquire additional certification credit for software that has been in service a length of time. PSH is defined in DO-178C as "A continuous period of time during which the software is operated within a known environment, and during which successive failures are recorded". To date, PSH has been successfully used to supplement certification evidence as long as three requirements are met: PSH relevance must be demonstrated, must be sufficient and in-service problems must be collected and analyzed [38].

Usually, PSH is applied to software that was not totally compliant to DO-178C, which is the case of AI applications. Thus, considering the three stated requirements when designing the AI-based solution will make possible a successful claim of PSH in the future to gain extra certification credit.

DO-178C traceability exception

A novelty introduced by DO-178C corresponds to how to handle object code generated by a compiler which is not directly traceable to the source code. When compilers translate source code to object code, they produce additional lines of code to handle exceptions, error detection or code for object-oriented

features, among others. However, these additional lines are not traceable to source code. Thus, subsection 6.4.4.2.b of DO-178C focused on how to address this exception on traceability, which usually requires additional verification efforts.

Then, DO-178C makes an exception to certify Level A software which does not totally comply with the bi-directional traceability requirement, the case of AI-based applications. However, in order to overcome this deficiency, developers must keep in mind that supplemental verification evidence must be demonstrated to achieve acceptability.

Proposed enhanced vision AI-based navigation architecture

In this section a preliminary architecture for a vision-based navigation approach applying AI techniques is presented. The main idea is to apply all the concepts seen so far not only to achieve an accurate, reliable, and robust application, but also to design a high operational range solution while considering the reviewed certification guidelines.

In order to establish the specific requirements of the navigation solution, it is necessary to understand the whole range of operations that AAM is expected to cover. To date, at least 36 potential use cases across 16 market categories have been identified encompassing from air commute services, to emergency first response or goods delivery [39]. Then, the necessity of every service enormously varies from one to the other. Thus, while it is true that not all them must satisfy the same requirements, the following ones have been identified to be desirable in all use cases:

- **Safety**: only self-contained solutions, which do not depend on external systems, will be considered, avoiding external attacks.
- **All-weather functionality**: the final solution must be able to operate independently to the light and weather conditions.
- **Real-time operation**: the computational cost required by the final approach must be adequate to provide solutions in real time.
- **SWaP requirements**: the final solution must be easy to integrate, aircraft agnostic and comply with low SWaP restrictions.
- **Level of performance**: the final approach must provide the accuracy, robustness and resilience required for AMM operations.
- **Future certifiability**: in order to ease the further solution certification, the elements and tools mentioned for additional certification credits will be contemplated.

Hardware selection

According to the first requirement in the above list, the technologies which are not self-contained are directly discarded, that is GNSS, VOR, DME, Pseudolites, LEO satellites and SoO. Moreover, because of its advantages, among the remaining possibilities, the technology chosen to be the principal one corresponds to the visual camera. However, some shortcomings must be handled to achieve the mentioned requirements:

- Scale uncertainty: three complement technologies are available to overcome this limitation: stereo cameras, LIDAR and altimeter. The first option requires a complex calibration while the depth accuracy is not suitable enough. The second option, LIDAR, is difficult to integrate, expensive and does not comply with the SWaP requirement. Thus, the altimeter is the option chosen to deal with depth estimation.
- Texture / light dependency: LIDAR, infrared, and near-infrared cameras deal with these concerns. LIDAR is discarded because of the reasons mentioned above. Then, among the optical solutions, infrared is chosen because it is the most extended and easy to acquire solution.
- Blur images in high-dynamical systems: IMU technology is the best complementary candidate due to its high acquisition rate and robustness in high-dynamical systems.
- High computational cost: Although GPUs excel at parallel processing, it is at the expense of energy efficiency. However, FPGAs offer hardware customization, which allows great performance and low latency at a low power consumption [40].

Summarizing, the selected hardware corresponds to: a visual camera, an infrared camera, a laser altimeter and an IMU device, all of them managed by a FPGA unit. Moreover, it should be noted that the proposed hardware allows to increase its accuracy in critical situations such as the approach or landing phases using

complementary landmarks or IR signs placed on the ground, near to the landing points.

Software selection

The proposed software architecture is depicted in Figure 4. As we can see, two redundant models (a hybrid and an end-to-end), are suggested to perform the same tasks, that is, estimate the aircraft pose. Although the goal of both models is the same, both are implemented using different techniques, following the redundancy and dissimilarity guidelines. Thus:

- **End-to-end model**: a recurrent CNN (RCNN) will be in charge of computing the pose estimation from sequential sensor inputs. Specifically, the CNN extracts visual features from consecutive visual and infrared images while the RNN models the temporal correlation of these features and the rest of the sensors to estimate the final pose.
- **Hybrid model**: the pose estimation is carried out by different modules, marked in dark teal in the Figure 4:
  - Sensor fusion: the fusion of the data from the different sensors can be implemented using CNNs, RNNs or even traditional methods such as Kalman or particle filters. The optimal method will depend on the nature of every sensor.
  - KeyPoints detection & matching: a CNN will be applied to analyze and extract high-level features from the images, increasing the capabilities against unknown environments.
  - Motion estimation: a RNN will model the motion dynamics from the fused measurements in order to preliminary estimate the aircraft pose.
  - Local Optimization: a NN will be applied to handle the data association problem related to optimizing the final result using the current image and all the images connected to it in the graph.
  - KF Culling: an optional module in charge of discarding redundant information so that the subsequent steps can be performed more efficiently.

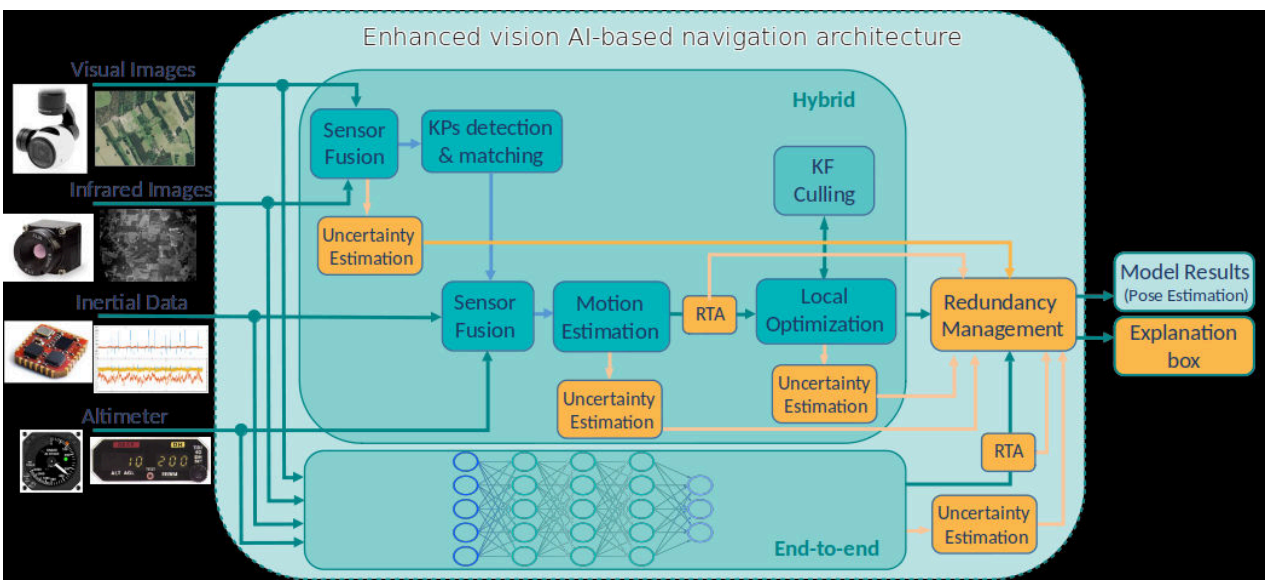

Figure 4. Software architecture of the proposed vision-based navigation solution

On the other hand, all elements in orange are control elements added to facilitate the solution certifiability.

- Uncertainty estimation: modules focused on compute the uncertainty of each estimation.
- RTA: control elements added to monitor the outcomes of the algorithm. The aircraft constraints and the flight dynamic will be used to set the thresholds which will alert about a model's malfunction.
- Redundancy Management: the main control element. It will receive all control information in order to select the most reliable result.

Moreover, it will prepare the Explanation box using all the data available.

- Explanation box: according to the XAI guideline, it corresponds to a description of the final outcome to increase the user's reliability. This description will gather the uncertainty related to every estimation as well as other internal control information.

Finally, the module Model Results will provide the final result, the pose estimation. Although three redundant elements are deseable according to redundancy recommendations, the computational cost will probably be quite large. However, considering all the control elements added, it is expected not only to detect, but also to identify any source of errors.

Conclusions

The major opportunity that AI techniques represent for the aviation industry due to their great potential has put the spotlight on their certifiability discussion. On the other hand, the demanding scenarios proposed by AAM operations require advanced technologies able to overcome traditional limitations. Thus, the use of AI algorithms in real applications is becoming fundamental, pushing to accelerate their certification path. However, traditional certification procedures are not prepared for adaptive solutions, which are not compliant with traceability or coverage requirements. Then, alternative certification procedures must be considered enabling the homologation of systems based on AI techniques while ensuring their maximum level of safety.

In this context, this work presents an AI-based architecture for a navigation solution aligned with the current direction of civil aviation certification procedures. The proposed design not only aims to be compatible with current certification requirements for its further use in real operations, but also to provide an accurate, resilient and robust performance in a wide range of AAM scenarios.

While it is well known that GNSS-based solutions, or their ground-based or low orbit alternatives, will remain a main part of the aerial navigation solutions, it is also true that they are vulnerable to external disturbances, making them not reliable enough. Consequently, dissimilar technologies are required to detect, at least, degradation performance, guaranteeing the integrity of the whole system. In this context, enhanced visual solutions provide a distinct advantage since their self-contained condition makes them immune to natural or deliberate distress. Thus, enhanced visual solutions are not the only or the best solutions but, to the best of our knowledge, they are the uniques which comply with all desirable requirements previously identified for AAM scenarios.

References

[1] Fayyad, Jamil, et al., 2020, Deep Learning Sensor Fusion for Autonomous Vehicle Perception and Localization: A Review, Sensors 20, 4220.

[2] Youn, Wonkeun, et al., 2015, Software Certification of Safety-Critical Avionic Systems: DO-178C and Its Impacts, Aerospace and Electronic Systems Magazine, IEEE. 30. pp 4-13.

[3] Chen, Changhao et al., 2020. A Survey on DL for Localization and Mapping: Towards the Age of Spatial Machine Intelligence.

[4] Cofer, Darren, 2021, Unintended Behavior in Learning-Enabled Systems: Detecting the Unknown Unknowns, IEEE/AIAA 40th Digital Avionics Systems Conference (DASC), 2021, pp. 1-7.

[5] Menon, Harsh et al., 2018. Deep-Learning based Approaches to Visual-Inertial Odometry for Autonomous Tracking Applications, SID Symposium Digest of Technical Papers., 49, pp. 471-474.

[6] Forster, Christian, Matia Pizzoli, Davide Scaramuzza,, 2014, SVO: Fast semi-direct monocular visual odometry, 2014 IEEE International Conference on Robotics and Automation (ICRA), pp. 15-22.

[7] Mur-Artal, Raul et al., 2015, ORB-SLAM: A Versatile and Accurate Monocular SLAM System, IEEE Transactions on Robotics, 31, pp. 1147-1163.

[8] Gao, Xiang et al., 2018, LDSO: Direct Sparse Odometry with Loop Closure, International Conference on Intelligent Robots and Systems.

[9] Klein, Georg, David William Murray, 2017, Parallel Tracking and Mapping for Small AR Workspaces, 6th IEEE and ACM International Symposium on Mixed and Augmented Reality.

[10] Wang, Sen et al., 2017, DeepVO: Towards end-to-end visual odometry with deep Recurrent Convolutional Neural Networks, IEEE International Conference on Robotics and Automation (ICRA).

[11] Costante, Gabriele, Thomas A. Ciarfuglia, 2018, LS-VO: Learning Dense Optical Subspace for Robust VO Estimation, IEEE Robotics and Automation Letters, pp. 1735-1742.

[12] Yin, Zhichao, Jianping Shi. 2018, GeoNet: Unsupervised Learning of Dense Depth, Optical Flow and Camera Pose, IEEE/CVF Conference on Computer Vision and Pattern Recognition.

[13] Clark, Ronald et al, 2017, VINet: Visual-Inertial Odometry as a Sequence-to-Sequence Learning Problem, AAAI.

[14] Chen, Changhao et al., 2019, Selective Sensor Fusion for Neural Visual-Inertial Odometry, IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), pp. 10534-10543.

[15] Chen, Danpeng et al, 2021, RNIN-VIO: Robust Neural Inertial Navigation Aided Visual-Inertial Odometry in Challenging Scenes, IEEE International Symposium on Mixed and Augmented Reality.

[16] Sheikhpour, Soroush, Mohamed Maher Atia, 2019, Calibration-free Visual-Inertial Fusion with Deep Convolutional RNNs, Proceedings of the 32nd International Technical Meeting of the Satellite Division of The Institute of Navigation.

[17] Dai, Kun et al., 2021, Loop Closure Detection Using KPCA and CNN for Visual SLAM, 40th Chinese Control Conference, pp. 8088-8093.

[18] Cascianelli, Silvia et al., 2017, Robust visual semi-semantic loop closure detection by a covisibility graph and CNN features, Robotics Auton. Syst. 92.

[19] Zhao, Chaoqiang et al., 2020, Monocular depth estimation based on deep learning: An overview, Science China Technological Sciences, pp. 1-16.

[20] Jing, Longlong, Yingli Tian, 2021, Self-Supervised Visual Feature Learning With Deep Neural Networks: A Survey, *IEEE Transactions on Pattern Analysis and Machine Intelligence* 43.

[21] RTCA, 2011, DO-178C Software Considerations in Airborne Systems and Equipment Certification.

[22] Youn, Wonsang et al., 2015, Software certification of safety-critical avionic systems: DO-178C and its impacts, IEEE Aerospace and Electronic Systems Magazine 30, pp. 4-13.

[23] Dmitriev, Konstantin et al., 2021, Toward Certification of Machine-Learning Systems for Low Criticality Airborne Applications, IEEE/AIAA 40th Digital Avionics Systems Conference (DASC).

[24] Sutthithatip, Sujitra et al., 2021, "Explainable AI in Aerospace for Enhanced System Performance, IEEE 40th Digital Avionics Systems Conference.

[25] Cofer, Darren D., 2021, Unintended Behavior in Learning-Enabled Systems: Detecting the Unknown Unknowns, IEEE/AIAA 40th Digital Avionics Systems Conference (DASC), pp. 1-7.

[26] Delseny, Hervé et al., 2021, White Paper Machine Learning in Certified Systems.

[27] Mark A, Skoog, 2020, Leveraging ASTM Industry Standard F3269-17 for Providing Safe Operations of a Highly Autonomous Aircraft, Federal Aviation Administration.

[28] ASTM International, 2017, ASTM F3269-17: Standard Practice for Methods to Safely Bound Flight Behavior of Unmanned Aircraft Systems Containing Complex Functions.

[29] Cofer, Darren D. et al., 2020, Run-Time Assurance for Learning-Enabled Systems, NFM.

[30] Kailkhura, Bhavya et al., 2019, Reliable and explainable machine-learning methods for accelerated material discovery, Computational Materials, 5, pp. 1-9.

[31] Downer, John, 2009, When failure is an option: redundancy, reliability and regulation in complex technical systems, LSE Research Online Documents on Economics.

[32] FAA Report, 2012, DOT/FAA/AR-11/28: Flight-Critical Systems Design Assurance.

[33] Doran, Hans D, Monika Reif, 2020, Examining Redundancy in the Context of Safe ML.

[34] SAE International, 2021, AIR6988 - Artificial Intelligence in Aeronautical Systems: Statement of Concerns, Aerospace Information Report.

[35] Samek, Wojciech et al., 2019, Explainable AI: Interpreting, Explaining and Visualizing DL.

[36] Cassenti, Daniel, Lance M. Kaplan, 2021, Robust uncertainty representation in human-AI collaboration, Defense + Commercial Sensing.

[37] Abdar, Moloud et al., 2021, A Review of Uncertainty Quantification in DL: Techniques, Applications and Challenges, Inf. Fusion 76..

[38] Rierson, Leanna, 2013, Developing Safety-Critical Software: A Practical Guide for Aviation Software and DO-178C Compliance.

[39] Booz Allen Hamilton, 2018, Urban Air Mobility (UAM) Market Study, Final Report.

[40] Qasaimeh, Murad et al., 2019, Comparing Energy Efficiency of CPU, GPU and FPGA Implementations for Vision Kernels, International Conference on Embedded Software and Systems.

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