Intelligent Autonomy for Aerospace Engineering Systems

Technologies from Different Application Domains to the Aviation Sector

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***Abstract*—The technological innovation on CNS and GNC in aviation and aeronautics creates the need not only for advanced automation but also more autonomy, and even intelligence to develop innovative aerospace engineering systems. This paper presents a varied summary of approaches for intelligent automation and autonomy from diverse operation and application domains. It deals with proposals from different computing and engineering disciplines as potential candidates to enable smart self-governance in next generations of air transport systems. The summary includes an important range of system integration architectures for Intelligent Autonomy (IA). They are relevant for CNS and GNC applications. The technologies discussed are meant to inspire architectures for intelligent and autonomous aerospace systems. The discussion focusses on biologically-inspired architectures as an attempt to provide human-like infrastructures for engineering systems that perform people's tasks. It explores challenges and opportunities as well as advantages and disadvantages for aerospace to develop CNS and GNC systems inspired by such architectures. Concluding remarks and the way forward to foster realization of IA solutions from varied domains for aerospace engineering are also presented.**

Keywords—aerospace engineering, artificial intelligence, robotics and autonomous systems, intelligent control architectures

I. INTRODUCTION

Aerospace engineering systems have undergone technological innovation improvements since first aircraft flights. In fact, air transportation systems have been safer since then. This inexorable evolution of the aviation industry involves upgrades and updates on Communication, Navigation, and Surveillance (CNS) systems of aircraft as well as Guidance, Navigation, and Control (GNC) systems for air vehicles. CNS enhancements mainly target enabling systems for aircraft operation such as Airspace Traffic Management (ATM).

Currently, the evolutionary CNS demand mostly comes from increasingly crowded airspaces where users from different aviation sectors (diverse aircraft and motives) try to make use of a common airspace whilst the GNC development is particularly focused on Unmanned Air Vehicles (UAVs). For both, CNS and GNC innovations, the aeronautical community is looking for more *intelligent* aerospace systems where *autonomy* plays a key role to keep air transportation safe and secure.

This paper presents a comprehensive synopsis of approaches for *intelligent automation* and *autonomy* in different operation arenas (land, sea, and air), and application domains (maritime, defense, enterprise, etc.). It briefly recaps and reviews proposals from diverse computing and engineering disciplines as potential candidates to enable self-governed high-integrity solutions for next generations of air transport systems. The summary includes a range of system integration architectures for Intelligent Autonomy (IA) which go from infrastructure management architectures for smart structures (immobile systems) to robotic control architectures for unmanned vehicles (mobile systems). They are two extreme types of man-made systems that have distinct nature. However, both are able to provide interesting reference architectures relevant to aeronautics since the former architectures are aligned with CNS applications and the latter architectures are aligned with GNC applications.

The state-of-the-art technologies from the above approaches are meant to inspire development of *intelligent* and *autonomous* aerospace systems. Their possible use in aerospace aims to facilitate, e.g. procurement and management of a shared multi-aviation airspace management and individual or collective AUVs. The discussion pays special attention to biologically-inspired architectures as an attempt to provide human-like infrastructure foundations for a clear distinction between hierarchical control layers identified in such architectural structures. It discusses challenges and opportunities when realizing technological *autonomy* solutions from other application domains in aerospace. The analysis presented reviews concepts of adjective terms related to self-governance such as *automatic*, *automated*, *autonomic*, and *autonomous*. Additionally, it explores computation paradigms for bottom-up/top-down integration such as sematic service orientation, and (multi-)agents as well as holistic computing organizations such as holarchy and swam *intelligence*.

This paper presents a cross-domain overview of *autonomy* technologies by highlighting advantages and disadvantages for their application in aerospace, and attractive application examples in aerospace inspired by the above technological approaches. The discussion presented includes comparison tables for the above technological approaches, and analysis results from *autonomous* behavior for operational aviation situations. It also includes concluding remarks and the way forward to foster *autonomy* solutions as integration architectures for aerospace engineering applications.

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The rest of the paper is organized as follows. Section II reviews concepts related to the term "auto" and *intelligence* in engineering systems. Section III discusses main drivers that inspire the most advanced IA architectures. Section IV discusses the three types of architecture defined by their scope. Section V discusses the most relevant existing man-made architectures for IA. Section VI discusses great challenges and opportunities to realize *intelligent* and *autonomous* architectures in UA Unmanned Aerial Systems (UASs). The final section presents the conclusions and future research directions.

II. Concepts and Terminology

This section reviews concepts related to the term "auto" and *intelligence* in engineering systems.

A. *The term "auto"*

There are four terms "auto" that are mainly used to mean independent behavior in man-made systems. Their meaning sometimes changes depending on the discipline they are used, other times they are use indistinctly. However, they have specific meaning within engineering and can also be applied to natural systems.

1) Automatic Systems

The adjective *automatic* is typically related and applied to characterize operational performance in machines or computers based on their actions. It is usually linked with self-operating mechanisms and a predetermined set of actions in engineered systems. However, going beyond engineering, the term *automatic* is used for spontaneous and involuntary reactions in other disciplines, e.g. reactive reflexes (or reflexive actions) from the human nervous system such as withdrawal reflexes when touching a very hot surface [1].

Automatic systems have a predefined sequence of action-based tasks which is known in advance (before the system works). The operational order to act is fixed (programmed) and cannot be changed on the fly (at runtime). Automata, well known in the industry and scientific community, are an example of an *automatic* approach for systems. The term *automatic* is applied to control systems, and also connected to another term: *automation*.

The term *automation* is widely used across many engineering sectors, e.g. industrial *automation*, home *automation*, and office *automation*. In the case of aerospace, flight deck *automation* helps pilots deal with many necessary tasks to operate aircraft [2]. Aircraft *automation* gets aviators rid of many operational tasks but also brings along problems related to safety, with considerable impact on air crashes [3]. The autopilot is part of the classic *automation* realized in aircraft, and it is an *automatic* system since the outputs automatically react according to the inputs.

2) Automated Systems

The adjective *automated* is typically related and applied to characterize operational performance in machines or computers based on the execution of their processes. It is usually linked with self-operating mechanisms where tasks are executed one after the other without human intervention.

Automated systems do not necessarily have a predefined sequence of tasks/sub-processes which is known before the system starts working. The operational order to carry out tasks can be either fixed or not fixed, and it can be changed on the fly. The execution process of automata is an automated approach. The term *automated* is also applied to control systems, and connected with *automation*.

The generation of waypoint for the aircraft autopilot system is an *automated* process. Additionally, the execution of the list of waypoints (airway) is also an *automated* process.

3) Autonomic Systems

The adjective *autonomic* is typically related and applied to characterize operational performance in machines or computers based on the way systems are self-managed. It is usually linked with self-managing mechanisms and the goal of being self-sufficient in engineering. However, going beyond engineering, it is also used for the set of involuntary responses needed to survive in other disciplines, e.g. human *autonomic* nervous system based on reactive reflexes [1]. In addition, IBM proposed the *autonomic* computing paradigm for management of Information Technology (IT) resources from computer systems that foresee users' needs [4].

Autonomic systems have a predefined set of responses that cannot be modified during runtime. There is no operational order to response as replies to stimuluses or cyclic responses can occur at any time or periodically, or even at the same time. Same inputs produces the same output. The term *autonomic* is applied to management systems, and connected with another term: *automicity*.

Conventional autopilot systems lack *autonomic* capabilities according to the above definitions. However, there are initiatives in aerospace to endow unmanned spacecraft and UAVs with *autonomic* capabilities [5], [6].

4) Autonomous Systems

The adjective *autonomous* is typically related and applied to characterize operational performance in machines or computers based on their decision-making processes [7] to take actions. It is usually linked with self-governing mechanisms and a non-predetermined set of actions in engineering. The term is also widely used in other disciplines, including to describe behavior in living organisms (biology) [1].

Autonomous systems respond to situations, moreover they are able to be aware of surroundings circumstances during runtime. There is no any particular operational order to make a response by means of tasks since replies to changes to a given situation are deliberately made on the fly. Same or different inputs can produce same or different outputs. Internal states and knowledge are considered (to make decisions) as additional inputs. The term *autonomous* is applied to control systems, and connected with another term: *autonomy*.

Aviation *autonomy* is at its early stages but it is making big and fast steps toward innovative enabling technologies. NASA provides its vision and roadmap to assure *autonomy* for aviation transportation [8]. There are also initiatives to endow aviation with true *autonomy* [9]-[13]. Conventional autopilot systems are not *autonomous* according to the above definitions.

B. Intelligent Autonomy

Capability, *autonomy*, and *intelligence* are three dimensions to assess behavior in Robotics and Autonomous systems (RASs). *Capability* is the system ability to effectively fulfil a specific activity (mission, operation, task, or action) in an environment. *Autonomy* is the system ability to autonomously make choices (select activities to do) and enforce the decision made. *Intelligent* is the system ability to accurately determine what activity maximizes the likelihood of achieving a goal successfully [14].

The above definitions means: (1) a system (e.g. robot) that can successfully carry out more complex activities (mission, operations, tasks, or actions) is maybe more *capable* than other systems (has more *capability*) but it does not mean it is more *autonomous* (has more *autonomy*) or *intelligent* (has more *intelligence*), (2) a system (e.g. mobile robot) walking randomly has *capability* and *autonomy* in choosing direction and distance but can fall down a staircase if it selects a wrong activity (has reduced *intelligence*), (3) a system (e.g. unmanned vehicle) doing wrong things successfully does not mean it has reduced *capability* but selecting autonomously wrong activities to be done means it has no *intelligence* but *autonomy*.

Intelligence has a range of interpretation according to disciplines and sectors where it is used. *Autonomy* and *intelligence* are key factors for decision-making processes. A genuine IA is able to come up with two or more different decisions (outputs) for the same input. Here, internal factors play a role to dissimilar outcomes, e.g. specific state in engineered systems as the stress factor is in humans (it sometimes affects pilots in crucial moments or situations).

III. Reference Architectures

This section discusses main drivers that inspire the most advanced IA architectures.

A. Inspirational Origins

Computer-controlled machines that carry out human tasks play an increasingly significant role in everyday life. The widely accepted prediction is that machines with IA will be ubiquitous man-made solutions in different domains. As a result of machines being capable of replacing persons in their activities, the natural inspiration to develop self-governed systems are human beings. This entails the full human architecture, including physical and behavioral aspects of the human body; physiology (human body) and psychology (human mind).

There are real-world applications that require architectural characteristics that are not fully covered by the human architecture, e.g. visual mimicry like those abilities of animals to change skin color and skin surface (camouflage) to resemble their surroundings. Additionally, there are autonomously coordinated collective behavior that is more effectively and efficiently provided by other species, e.g. swarms of birds or bees, and shoal of fishes. Thus, developers have mostly started looking at general biology for architectural approaches. This biological inspiration to develop self-governed systems gives place to so-called bio-inspired or biologically-inspired systems.

A more comprehensive science (such as biology) considers all types of lives and living organisms. This makes it possible to widen the spectrum of architectural solutions for the engineering problems, in particular those which require advanced and evolved system architectures for IA. *Intelligence*, tightly related to behavior (psychology), ultimately depends on physical biology; anatomy and physiology [15].

B. Philosophical Biology

Machines endowed with IT (controlled by computers) such as unmanned vehicles and smart factories/buildings are becoming progressively sophisticated by increasing their self-governing capabilities. They are able to carry out more complex tasks, and perform longer-term operations (e.g. space rovers for exploration of very big and hostile planet areas and non-stop production lines). In addition to advanced *autonomous* capabilities, they also requires operational resilience (e.g. fault recovery), and good management of resources (e.g. efficient energy consumption) to succeed in operational persistence. Most of the current bio-inspired RASs (including humanoids) are isolated solutions for specific problems but not integrated solutions for full adaptation to an unknown environment.

In addition to those specific and special capabilities which are not provided by the human architecture (mentioned in the previous subsection), researchers and practitioners have also started considering metaphors from definitions provided by philosophers who try to explain biological processes and phenomena from a philosophical viewpoint. These processes are attractive since they provide essential abilities to survive under adverse conditions, e.g. adaptation, reproduction, and evolution. The following philosophical biology concepts are mainly considered as inspirational paradigms for IA:

- <u>Homeostasis</u> [16]: self-regulation provided by organisms to maintain stable conditions (internal states based on external ones) for optimal living performance. Homeostatic processes are relevant for *autonomic* management to reinforce IA. There are some proposals for aircraft and spacecraft [6], [17]-[18].
- <u>Apoptosis</u> [19]: self-destruction of cells in multicellular organisms. This concept is potentially attractive for NASA space exploration missions as self-protection of *autonomic* agent-based systems [20].
- <u>Poiesis</u> [21]: reproduction or creation of living organisms. This concept is at its premature stages for RASs although some discussions have been made for *intelligent* robots [22].

There are other biological paradigms related to the way living organisms organized themselves such as holons (a part and a whole at a time) [23]. The holonic approach is of great interest in the RAS community as well as in computer science (e.g. agency structure). Original applications are in manufacturing systems [24]. Also, there are proposals for unmanned maritime vehicles [25], and UASs [9]-[10]. All the architectural approaches go beyond and complement the generic architecture for unmanned systems [26].

C. Architectural Approaches

The main architectures to engineer IA are inspired by biology of the domains of life as discussed in the previous subsection. The inspiration mainly focusses on animals (including humans). However, plants and even bacteria are included. The biologically-inspired approaches for operational persistence make sense since species have lived, evolved, and managed to survive for many years. Such abilities involve resilience as the essential capability to assure persistent existence. The particular importance are the functions of living organisms and their parts (physiology) as well as their behavior and mental processes (psychology).

The classification of architectural approaches for IA is based on the architecture scope. It is defined by splitting the levels of biological organization into three architecture types:

- Intra-architecture
- Inter-architecture
- Supra-architecture

The intra-architecture of reference looks at single biological structures, and entails biological granularity levels from atom to organism. The inter-architecture of reference looks at a single biological structure and its interaction with other entities (organisms), and entails the biological granularity level of population. The supra-architecture of reference looks at multiple biological structures, and entails biological granularity levels from community to biosphere.

IV. Biolgical Architectures

This section discusses the three types of architecture defined by their scope in subsection III.C.

A. Intra-Architecture of Reference

The intra-architecture of reference concerns the anatomy and conduct of all the living organisms individually, i.e. without taking into account organisms' interactions with each other. It mainly targets the internal aspects of the living-thing architectures. The intra-architecture approaches taken as reference from biology are mainly from animals and plants although the remaining kingdoms of the living organisms are an emerging inspiration (e.g. unicellular protist Paramecium caudatum [27]).

Animals (including human beings) can be vertebrates and invertebrates. The former are classically the most attractive in the RAS community although the latter have remarkably gained interest, e.g. ever-emerging insect-like robots. The attraction for the animal architecture does not make any distinction between viviparous animals (most of the mammals) and oviparous animals. However, the reproduction process has brought very little attention to develop systems architectures yet. The architectural aspects of interest are the physical structures (anatomy and physiology), and mental processes of the animals that make possible *intelligent* and self-governed behavior. This involves a wide spectrum for independent behavior which goes from *autonomic* management (e.g. nervous reflexes) to *autonomous* decision making (e.g. self-determined actions).

Plants can be non-vascular and vascular (seed or seedless). They are attractive for the RAS community at the point they have remarkably gained interest in the last decade, e.g. recently-emerging plant-like robots. The attraction for the plant architecture mainly lays on the way plants grow [28]. It does not make any distinction between seed plants and seedless plants. However, the reproduction process has not brought any attention to develop systems architectures yet. The architectural aspects are the physical structures (anatomy), and mental processes of the plants that make possible *intelligent* and self-governed behavior. This involves a wide spectrum for independent behavior which goes from *autonomic* management (e.g. survival mechanism such as mental toughness) to *autonomous* decision making (e.g. self-determined actions such as orientation of branches).

Table I shows some examples of the main capabilities of interest from the intra-architecture from living organisms.

TABLE I. Inspirational Intra-Architecture Capabilities

Biology			**RAS**
Level	***Kind***	***Ability***	***Capability***
Animal	Any	Mobility	Autonomous navigation
Plant	Any	Growth	Dynamic reconfiguration
Animal	Some animals & Humans	Deliberative grasping	Dexterous manipulation
Animal	Most of the animals	Eyesight	Computer vision
Animal	Animals & Humans	Cognition	Pattern recognition
Organ system	Immune system	Self-defense	Self-protection (Security)
Organ system	Endocrine system	Hormonal regulation	Self-regulation
Organ system	Nervous system	Hierarchical self-governance	Intelligent autonomy
Organ	Spinal cord	Reflex-driven regulation	Reactive behavior
Organ	Brain	Cognitive processing	Neural computation
Organ	Mind (brain)	Consciousness	Situation awareness
Tissue	Skin	Self-healing	Self-repairing
Cell	Neurons	Reconnection	Neural network

B. Inter-Architecture of Reference

The inter-architecture of reference goes beyond the intra-architecture and considers interfaces and interactions between living organisms. It mainly targets the external aspects of the living-thing architectures. The inter-architecture approaches taken as reference from biology are mainly from animals and plants.

The inter-architecture is the less used as a reference by the RAS community although it catches the attention of researchers and practitioners to develop RAS systems that actually interact with humans, e.g. service robotics (companion robots). Inter-communication between entities goes from physical interaction to social interaction [29].

Table II shows some examples of the main capabilities of interest from the inter-architecture from living organisms.

TABLE II. INSPIRATIONAL INTER-ARCHITECTURE CAPABILITIES

Biology			RAS
Level	***Kind***	***Ability***	***Capability***
Animal population	Dolphins	Acoustic communication	Acoustic underwater interaction
Plant population	Sunflowers	Sun following	Auto-tracking
Animal population	Anphibians	Aquatic and terrestrial life	Ground-water navigation
Animal population	Spiders	Shrinkage (curling up)	Reconfigurable protection
Plant population	Any	Energy conversion	Photovoltaic cell power generation

C. *Supra-Architecture of Reference*

The supra-architecture of reference concerns the conduct and in some cases the anatomy of all the living organisms collectively (as a whole rather than individually). It differs from the inter-architecture since the supra-architecture takes into account the interaction between living organisms that form a larger but single living entity (as a whole and as a part). Supra-architectures mainly target the internal aspects of the living-thing architectures (when considered as a whole) as well as external aspects (when considered a collection of smaller but single entities). They can be seen holistic structures and behaviors (holons as discussed in section III.B).

The supra-architecture approaches taken as reference from biology are the five kingdoms of the living organisms: (1) Monera (prokaryotes; unicellular organisms without a nucleus) [30]-[32], (2) Protista (unicellular organisms with a nucleus) [33], [34], (3) Fungi (fungus) [35], [36], (4) Plantae (plants) [37]-[39], and (5) Animalia (animals) [40]. The most popular inspirational supra-architecture from living organism in the RAS community is the swarm of animals, e.g. bee swarm. There are others such as shoals, flock, herd, and pack of animals that are also considered.

Table III shows some examples of the main capabilities of interest from the supra-architecture from living organisms.

TABLE III. INSPIRATIONAL SUPRA-ARCHITECTURE CAPABILITIES

Biology			RAS
Level	***Kind***	***Ability***	***Capability***
Animal community	Bees	Swarm flight	Collision-free navigation
Plant community	Climbing plant	Creeper grow	Autonomous guidance
Animal community	Some birds	V-shaped flock flight	Efficient navigation
Animal community	Ants colony	Food chasing (pheronomes)	Cooperative guidance
Animal community	Fishes	Shoaling	Collaborative and efficient navigation
Animal community	Ants	Big food transportation	Coordinated behavior
Ecosystem	Terrestrial/ Aerial/Acuatic	Cyclic collaboration	Collaborative behavior
Biosphere	Earth	Self-adaptation	Dynamically-adaptive behavior

V. INTELLIGENT AUTONOMY ARCHITECTURES

This section discusses the most relevant existing man-made architectures for IA.

A. *Robot Architectures*

IA involve RASs. UASs include mobile systems such as any GNC system in aeronautics, e.g. Unmanned Aerial Vehicles (UAVs) as well as immobile systems such as any CNS system in aviation, e.g. ATM. They can be considered either robots or *autonomous* systems. Hence, classical Robot Control Architectures (RCAs) can be applied to UASs. RCAs can entail hardware and software. However, this subsection only focuses on the software structure and organization of the RASs.

There are mainly three main types of RCAs: hierarchical RCAs, behavioral RCAs, and hybrid RCAs [41].

- Hierarchical RCAs are suitable to implement deliberative decision-making processes for high-level control (top layer of the RCA hierarchy). They are usually driven by the sense-plan-act paradigm. They have been used as an architectural solution of IA for different unmanned systems, including UAVs (e.g. multi-layer control architecture for IA in UAVs [9], [10], [42]).
- Behavioral RCAs are suitable to implement reactive decision-making processes for low-level control (bottom layer of the RCA hierarchy if it were a hierarchical RCA). They are usually driven by the sense-act paradigm, and belong to a group of RCAs so-called behavior-based architectures. Robotic functionalities wrapped to provide behaviors are linked to sensing inputs to command effecting outputs. Thus, this type of RCA offers no free will for robots to make decisions since behaviors (associated to combination of inputs) are triggered based on already-made decisions for the robot to act (output). They have also been used as an architectural solution of IA for different unmanned systems, including UAVs [43].
- Hybrid RCAs combine the two above RCAs. Thus, they are suitable to implement deliberative and reactive decision-making paradigms. They allow for the implementation of the three main layers from hierarchical RCAs: the deliberative layer (top), active (also executive) layer (middle), and reactive layer (bottom). Additionally, they allow for the realization of behaviour-based reaction from the behavioral RCAs that represent paradigms from the human architecture, e.g. a specific type of behavioral RCA like the sub which allows for the combination (summation) of behaviors with optional enabling selection mechanism. They have also been used as an architectural solution of IA for different unmanned systems, including UAVs [44].

Fig 1. shows the three main RCAs that can be found in robots from different domains (land, sea, and air) and their relation with the human control architecture driven by the nervous system.

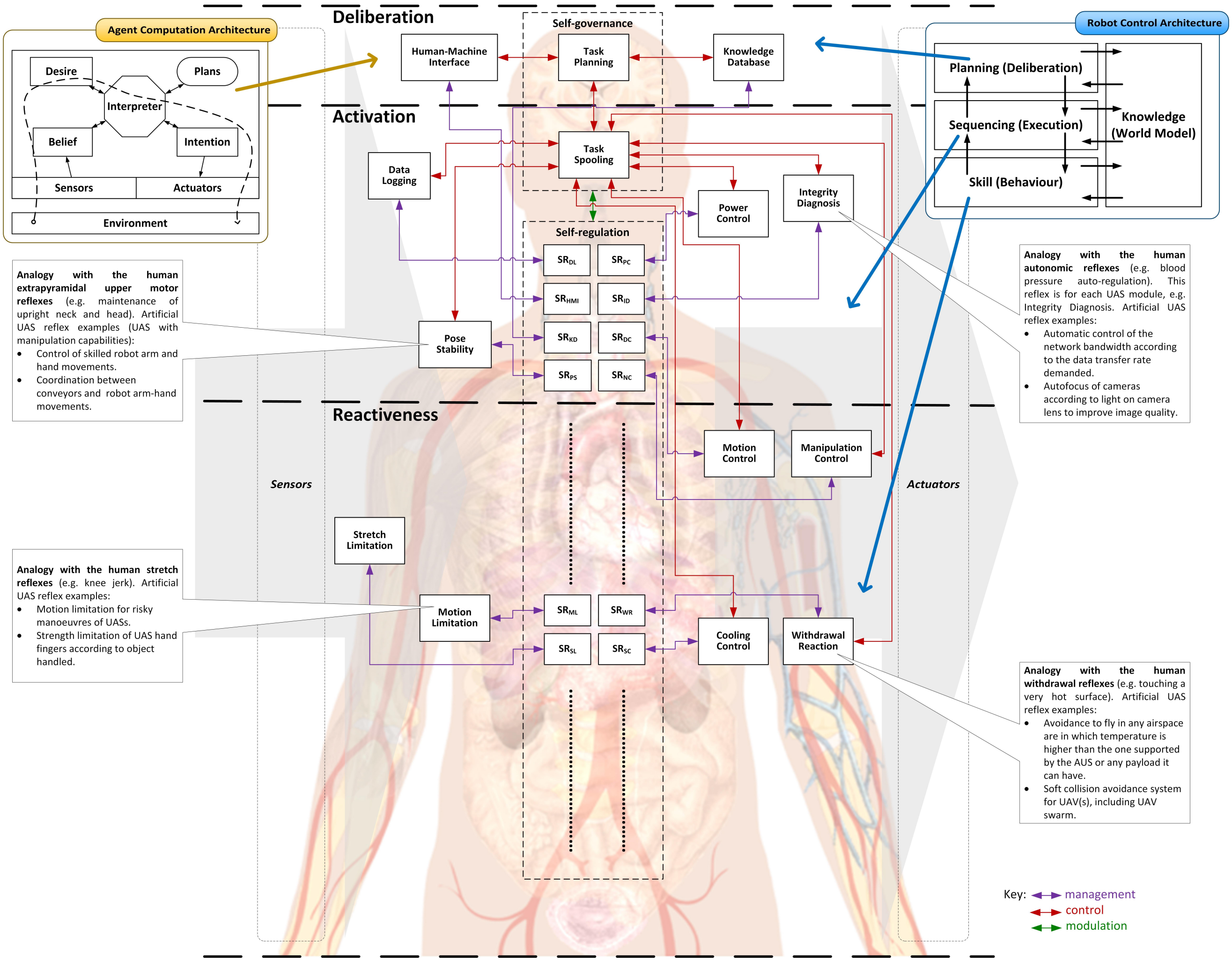

Fig. 1. Main Robot Control Architectures (RCAs) and the human control architecture

B. Agent Architectures

The degree of *intelligence* in *autonomous* entities varies. These entities are the building blocks of computation architectures, and can be classified as: workers, actors, agents, and holons. They are usually software entities from computer science although they can include a hardware part. Software workers have no many applications in IA because of their low degree of *intelligence*. Software actors [45] show some self-governance. However, they have limited capacity to make decisions autonomously, and often require considerable supervision. Software agents has been developed for many years, and are the most known and used in IT-based applications. They can be considered a Knowledge Technology (KT) if cognitive algorithms are used to implement them. Software agents are computing entities which have the ability to work by their own or as a whole at a time can be identified as holons (software and hardware) [46].

Agents have been attractive for researchers and practitioners as they are tempted to endow agents with intellectual human-like capabilities based on AI methods. They are originally IT software entities which provide developers with flexibility to be easily modified by means of computer programing. However, they have become widely accepted in other disciplines since they are deployed in computers to control devices and machines (i.e. embedded software moved away from classical IT systems). Thus, they can be currently considered be either software or hardware, or even both. They are an essential part for most IA solutions. RCAs can implement agent technologies in order to implement functionalities, including *automated* planning for sequences of UAS tasks/actions [10]. Self-governed agents are *autonomous*, sometimes *intelligent* pieces of software/hardware/software-hardware that are able to control the behavior of robots (e.g. UAV) without external influence or even little supervision.

Software agents and team of software agents (multi-agent systems) [47] have many applications in RAS (including well defined RCAs), with implementations in vehicles for land [48], sea [49], and air [50]. A middleware (to communicate agents with each other) is usually required for implementations of software agents, e.g. the Robot Operating System (ROS) [51].

Realization proposals of single or multiple agents include: (1) implementations of agents within a single platform (immobile or mobile system/subsystem/component) that is part of a larger system (e.g. a fleet of UASs), and (2) implementations of only one agent for the single platform. The former considers software agents as the essential elements of the infrastructure to support the whole single platform. Agents are assigned per functional module of the system. The latter considers software agents as the elemental components of the infrastructure to support the whole system. Thus, agents are assigned per functional platform of the system.

Single-agent solutions per platform aims to simplify the community of agents (also known as agency) but makes more complex the agent anatomy and interactions between agents. This increases computation required to implement agents. Multiple-agent solutions per platform aims to simplify the agent anatomy but makes more complex the agency. This increases interactions (communication) required to connect agents.

NASA uses multi-agent simulations for collaborative ATM based on simple route selection strategies and traffic flow management approaches [52]. Multi-agent systems have applications in traffic and transportation [53]. They are already implemented in Optimal Aircraft Sequencing using *Intelligent* Scheduling (OASIS) [54]; .also considered for next generations for ATM systems [55].

C. Architecture Algorithms

AI has provided many algorithms for computation of IA. Algorithmic approaches model functionalities and capabilities from biological architectures as those discussed in section IV. They implement the information processing logic based on biology in order to realize a range of natural abilities. Realizations go from human mind abilities (high control level) such as learning, planning, reasoning, and understanding to *autonomic* management capabilities of the spinal cord (low control level) such as self-regulation, self-protection, and self-optimization. Additionally, other biological capabilities such self-healing as well as genetic mutation, plant structures (lindenmayer systems [56]), and bacterial colonies.

Computational approaches also include machine learning methodologies in an effort to mimic learning abilities from animals (including humans). These algorithmic solutions involve so called neural networks as an attempt to replicate neurons and the nervous system from animals to support IA learning. Machine learning methods can be based on data representation [57] or specific tasks. The former is tightly related to deep learning [58] where learning mainly depends on different degrees of supervision (suitable for neural networks [59]). The latter does focus on particular tasks rather than representations (features) to detect and classify raw data as the former does.

D. Architectural Technologies

Table IV summarizes the most relevant IA architectures currently used and proposed for UASs.

TABLE IV. UAS INTELLIGENT AUTONOMY ARCHITECTURES

Architecture			Application	
Name	***RCA***	***CA***	***Capability***	***Platform***
OASIS [54]	N/A	Agent-based	CNS	Airport
TRAC [60]	HRCA	Agent-based	GNC	UAVs
APEX [61]	HRCA	Agent-based	GNC	Unmanned helicopter
HAIC [62]	HRCA	None	Navigation	UAVs
WITAS [63]	HRCA	Object-oriented[a]	GNC	Unmanned helicopter
OCP [64]	HRCA	Object-oriented[a]	GNC	UAVs
BBSFA [65]	BRCA	Agent-based	GNC	UAVs

[a.] Programming paradigm (software architecture) not discussed in the computation architectures.

Table V summarizes interesting IA architectures from different application domains for potential use in UASs. They are architectures from the Intelligent Vehicle Control Architecture (IVCA) [66], Holonic Manufacturing Systems (HMS) [67], Artificial Immune System (AIS) [68], *Autonomic* Computing (AC) [69], Organic Computing (OC) [70], Viable System Model (VSM) [71], Swarm *Intelligence* (SI) [72], Artificial Endocrine System (AES) [73]

TABLE V. INTELLIGENT AUTONOMY ARCHITECTURES FOR UASS

Intelligent Autonomy Architecture				Potential Application	
Name	***Pattern***	***Algorithm***	***Domain***	***Platform***	***Pros/cons***
IVCA [66]	HRCA & Agent	Ontologically-reasoned	Maritime	Airports, UAVs	Open architecture Complex distributed planning
HMS [67]	Holon	Ontologically-reasoned	Production	Airports, Aircraft	Massive integration Not clear realization
AIS [68]	Artificial cell	Evolutionary	AI	Airports, Aircraft	Cybersecurity Complementary architecture
AC [69]	MAPE	Heuristic	IT	Airports	Scalability Complementary architecture
OC [73]	Obs-Ctlr	Model-based	IT	Airports	Scalability Not clear realization
VSM [71]	Reflex-driven	Heuristic	Enterprise	Airports, Aircraft	Management Complementary architecture
SI [72]	Holon	Metaheuristic	Robotics	UAVs	Coordinate behavior Complex algorithms
AES [73]	Artifical hormone	Evolutionary	AI	Airports, Aircraft	Self-regulation Complementary architecture

The domain shown in Table V for AIS, AC, OC, SI, and AES is the original one. However, all of them have applications in different domains such as industrial *automation* [74], defence, transportation [75], aerospace, and healthcare.

VI. Challenges and Opportunities in Aviation

This section discusses great challenges and opportunities to realize *intelligent* and *autonomous* architectures in UASs.

A. Assimilation of Coexistence

It was unthinkable to IA in UASs few decades ago. Nowadays, UASs are already part of the aviation community, e.g. an increasing number of *autonomous* UAVs (some of them are experimental but also serious approaches). However, the incorporation of *intelligence* to UAS decision-making processes to, for instance, either navigate in the case of UAVs [9], [50] or control the air traffic [76] is still at very early stages. The definition of *intelligence* (*intelligent* systems) and *autonomy* (*autonomous* systems) is very well known and accepted in communities such as RASs and AISs for different application domains (ground and sea). Such definitions are absolutely new for aeronautics as there are still aviation stakeholders who use indistinctly the adjective "unmanned" and "autonomous". Moreover, an *intelligent* and *autonomous* UAS is still currently unimaginable from the safety viewpoint. This is the most complex issue to tackle since it will demand a huge effort to assure *intelligent* and *autonomous* UASs are safe to be used.

Computer-controlled machines, and even stand-alone computers carrying out autonomously human tasks are currently quite used, and will be seen more and more as IA-endowed RAS solutions for next generations of *intelligent autonomy* across different application domains. This increases society concerns as to dependability for the interaction between humans and machines/computers. Here, any *intelligent* and *autonomous* UAS, like other RASs, faces the problem of coexistence with other aviation systems. This is a societal issue which ultimately brings along morality and ethics for actions taken based on *autonomous* decisions made. This matter has already brought the attention to be investigated in aviation for UASs [13].

B. Requirements Analysis and Design

The modelling and simulation of *intelligent* and *autonomous* UASs carried out at early stages of their development lifecycle are crucial for such complex systems. They demand more effective and efficient engineering tools to deal with the definitions as well as specifications of emerging UASs. This also includes the setup of an analysis and design framework to facilitate the early evaluation of the UAS under development. A multidisciplinary framework to facilitate the analysis and design *autonomous* UASs becomes essential due to the number of disciplines involved in the development of such systems [77]. Future modelling and simulation environments can either be updates on existing tools or development of new tooling approaches as needed.

The analysis and design of IA for UASs require a strong interaction between computer science and engineering. IA solutions for UASs move away from classical engineering approaches to develop systems to now incorporate more specialized computation. However, systems engineering principles will be still applied to simplify the development and management processes of such systems.

C. Evaluation and Certification

Verification is one of the most challenging issue for IA no matter the domain unmanned systems are coming from. The problem is that a truly *intelligent* and *autonomous* system can have too many combinations of different output(s) for the same input(s). This makes very difficult the generation of all the possible combinations for the above inputs and outputs. Additionally, it can have the different outputs for the same set of inputs which makes IA behavior tough to predict. Thus, UAS are rather unpredictable, and even worse they become non-determinist; a definitely unwanted quality property for safety, in particular in aviation. A promising approach that researchers propose to use to verify IA is formal methods such as model checking. However, the application of this verification method reduces the solution space since it limits the above input-output relation (combination).

Validation of IAs is reasonably meaningless as verification gets complicated and cannot be done in full. It also suffers the same limitations verification has. This raises concerns about how reliable and robust IA systems can be which ultimately has an impact on the certification of IAs. The challenge set by the verification, validation, and certification of IA for UASs creates a good opportunity to develop innovative methodologies or tools. They are some approaches used for IAs from other domain. However, they could be correctly applied to UASs in aerospace, e.g. *autonomous* ground vehicles [78]. Along with the above aviation safety issue, there is also an actual concern on aviation security, in particular cybersecurity which has an impact on IA for UASs.

Additionally, uncertainty plays a key role in the evaluation (verification and validation) and ultimately certification of IA for UASs. Everything related to uncertainty has its root in the sensing system (sensors). Sensation is a critical pre-stage in the chain "perception-comprehension-projection" of Situation Awareness (SA) taken into account in IA decision making processes. Uncertainty is considered by means of information sensitivity in a decision-making support proposal for avionics analytics [11].

D. Highly-Skilled Multi-Disciplinary Team

The need for a highly-skill team to develop IA for UASs goes beyond specialist from mechatronics or even robotics. These IA systems require not only developers from mechanical, electrical, electronic, and control engineering but also from other completely different disciplines such as psychology (due to the self-governed behavior), and advocacy (moral and ethical issues related to IA).

IA demands highly-skilled stakeholders. The main challenge are multidisciplinary teams that can be geographically dispersed. This creates an opportunity to envisage tools to facilitate the development of AI solutions. There are already initiatives to tackle the above issues: (1) a design framework to cross-check models (pre-verification) since stakeholders have their owe model of the UAS under development which can differ (in nature) from other stakeholders [79], and (2) a distributed development framework for remote integration of high-integrity UASs [80].

VII. CONCLUDING REMARKS

A comprehensive synopsis of approaches for *intelligent automation* and *autonomy* has been presented. Proposals from diverse computing and engineering disciplines as potential candidates to enable self-governed high-integrity solutions for next generations of UASs have been briefly recapped and reviewed. The summary has include a range of system integration architectures for IA. It has provided interesting reference architectures relevant to aeronautics, aligned with CNS and GNC applications. The cutting-edge technologies presented have been meant to inspire development of *intelligent* and *autonomous* aerospace systems, e.g. as to procurement and management of a shared multi-aviation airspace management and individual or collective AUVs. The discussion has paid special attention to biologically-inspired architectures as an attempt to provide human-like infrastructure foundations. Challenges and opportunities when realizing technological *autonomy* solutions from other application domains in aerospace have been discussed. Concepts and computation paradigms related to IA have been discussed. A cross-domain overview of *autonomy* technologies, highlighting advantages and disadvantages for their application in aerospace has also been discussed. It has included a comparison of technological approaches, and analysis results from *autonomous* behavior.

Future work will include case studies with concrete application scenarios to show how the IA technology presented in this paper can be technically applied to UASs. Enabling tools to develop UASs will be also discussed.

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