Intelligent Systems: Shaping the Future of Aeronautics and Space Exploration

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Abstract: Intelligent systems are nature-inspired, mathematically sound, computationally intensive problem solving tools and methodologies that have become important for NASA's future roles in Aeronautics and Space Exploration. Intelligent systems will enable safe, cost and mission-effective approaches to aircraft control, system design, spacecraft autonomy, robotic space exploration, and human exploration of Moon, Mars, and beyond. In this talk, we will discuss intelligent system technologies and expand on the role of intelligent systems in NASA's missions. We will also present several examples of which some are highlighted in this extended abstract.

Keywords: Intelligent systems, Intelligent control, Adaptive control, Artificial Intelligence, Aircraft Control, Evolvable hardware.

1. Introduction

Intelligent systems as envisioned today are mostly modeled after rationalistic AI. They examine intelligent behavior using the models of human systems that enable intelligent behavior. The need for intelligence is driven by the need for:

1. Learning and reasoning (modeling and representation)
2. Adaptability (unknown situations and/or fault accommodation)
3. Robustness across problem domains and/or uncertainties
4. Improving efficiency (over time and/or space)
5. Information compression (data to knowledge)

Intelligent System (IS) applications have gained popularity among aerospace professionals in the last decade due to the ease with which several of the IS tools can be implemented. In addition to this ease of implementation, IS has been shown to solve difficult problems more efficiently. Another advantage that IS practitioners have seen is complex ideas can be implemented and tested with rapid development cycles.

The role of intelligent systems in NASA's missions is two-fold: (1) function as intelligent assistants to augment human expertise; (2) act as a substitute for human expertise in endeavors that are remote and/or save cost, time, and life. For example, intelligent systems assist humans in solving difficult optimization problem by their shear ability to robustly search through myriad of choices. In contrast, intelligent systems are also used on autonomous flyers and rovers as human substitutes.

In the next sections, we outline some of the technologies and applications that are being pursued at NASA Ames in the realm of intelligent systems. These technologies include: intelligent control using neural networks; intelligent fault detection using artificial immune systems; and automated design using evolutionary algorithms.

2. Fault-adaptive Intelligent Control

In the last 30 years, at least 10 aircraft have experienced major flight control system failures claiming more than 1100 lives [1,2]. The Intelligent Flight Control (IFC) research program began in 1992 to address the need to examine alternate sources of control power to accommodate in-flight control system failures. The major feature of IFC technology is its ability to adapt to unforeseen events through the use of a self-learning neural flight control architecture. These events can include sudden loss of control surfaces, engine thrust, and other causes that may result in the departure of the aircraft from safe flight conditions.

The NASA Ames Intelligent Flight Controller uses a neural flight control architecture that is based upon the augmented model inversion controller (See Figure 1). This direct adaptive tracking dynamic inverse controller integrates feedback linearization theory with both pre-trained and on-line learning neural networks. Pre-trained neural networks are used to provide estimates of aerodynamic stability and control characteristics required for model inversion. On-line learning neural networks are used to generate command augmentation signals to compensate for errors in the estimates and from the model inversion. The on-line learning neural networks also provide additional potential for adapting to changes in aircraft dynamics due to damage or failure. Reference models are used to filter command inputs in order to specify desired handling qualities. A Lyapunov stability proof guarantees boundedness of the tracking error and network weights. Successful piloted simulation studies were also performed at NASA Ames Research Center on a commercial transport aircraft simulator [3-5]. Subjects included both NASA test pilots and commercial airline crews.

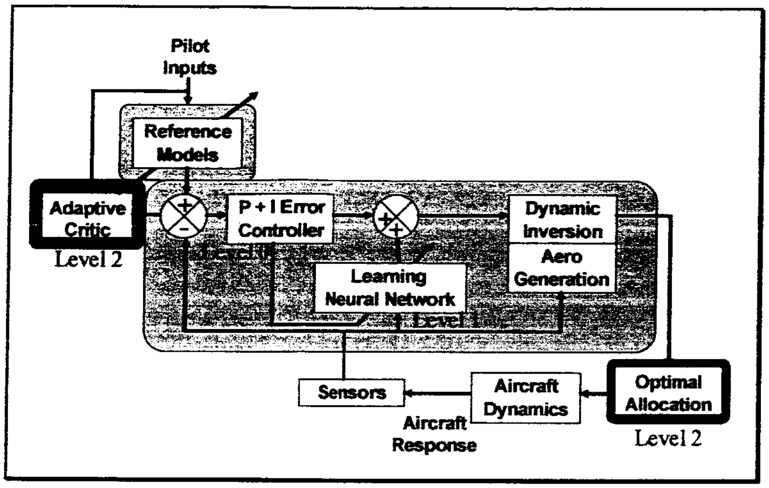

Figure 1: Intelligent flight control architecture

3. Intelligent Control for an EAV

Fast-moving airplanes designed to navigate Mars the way insects control their courses on Earth might one day travel to places where exploration rovers and landers cannot reach. Mars is covered with intriguing canyons, cliffs, and craters, most of them too remote or hazardous for conventional exploration vehicles to reach. Exploration Air Vehicles (EAVs) could carry cameras and other sensors to these spots. Building a Mars EAV will provide a new way for NASA to conduct exploration. In addition to exploration of hard to reach spaces, EAVs could relay information between rovers already exploring the planet's surface or monitor a spacecraft while it touches down.

The NASA JPL-led Mars EAV project is named BEES, for Bio-inspired Engineering of Exploration Systems, and has been in the works for a few years. The plane is called a biomorphic flyer because it captures some of nature's successful flight designs -- in this case, unique strategies of navigation, hazard avoidance and flight -- and combines them with conventional designs. The BEES technology is based on the fact that insects like the honeybee and the dragonfly possess a brain with less than 0.01 percent the neurons found in a human brain, yet with simple strategies they navigate in the world just fine.

Putting a plane on Mars poses several challenges. For one, the atmosphere on Mars is so thin that flying an aircraft near the surface is difficult, like trying to control a plane 100,000 feet above the Earth's surface. And because Mars is mostly unexplored, an unpiloted aircraft would need to have the ability to sense and respond to what it encounters.

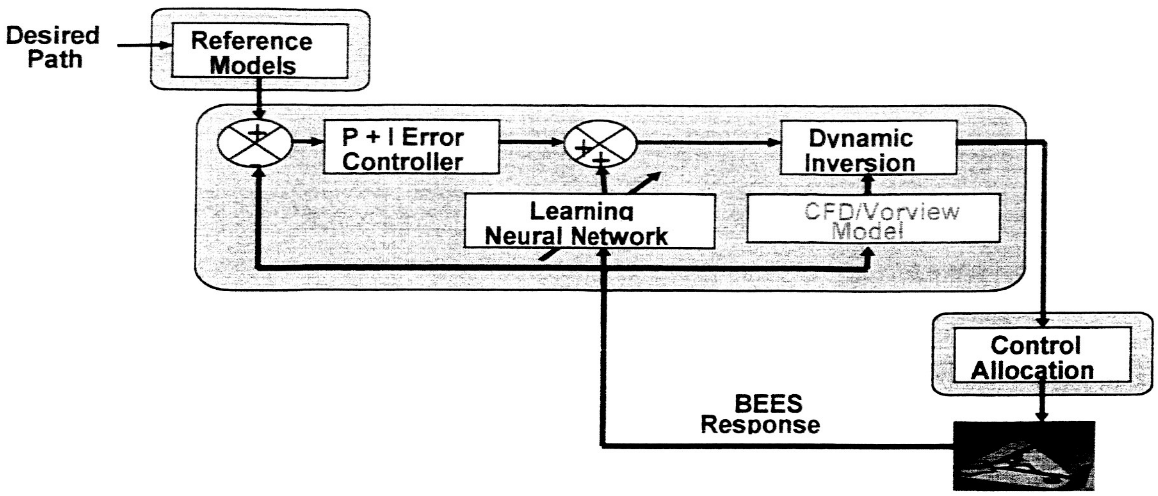

Figure 2. EAV Adaptive Control Architecture

At NASA Ames, we have developed and demonstrated an adaptive control architecture (Figure 2) that can enable a stable Martian flight in the midst of uncertainties and failures [9].

4. Immunity-based Fault Detection

An immunity-based approach incorporates the knowledge of the normal operational behavior of a system from sensory data, and probabilistically generates a set of pattern detectors that can detect any abnormalities (including faults) in the behavior pattern indicating unsafe operation. We developed a tool called MILD (Multi-level Immune Learning Detection) based on a real-valued negative selection algorithm that can generate a small number of specialized detectors (as signatures of known failure conditions) and a larger set of generalized detectors for unknown (or possible) fault conditions.

The negative selection algorithm is based on the principles of self-non-self discrimination in the immune system. The negative-selection algorithm can be summarized as follows [6-8]:

- Define self as a collection S of strings of length l over a finite alphabet, a collection that some way models the normal operation (or system behavior). For example, S may represent the normal operating conditions of an aircraft.
- Generate a set R of *detectors*, each of which fails to match any string in S. Instead of exact or perfect matching, the method uses an approximate matching rule, in which two strings match if and only if they are within a certain distance r, where r is a suitably chosen parameter.

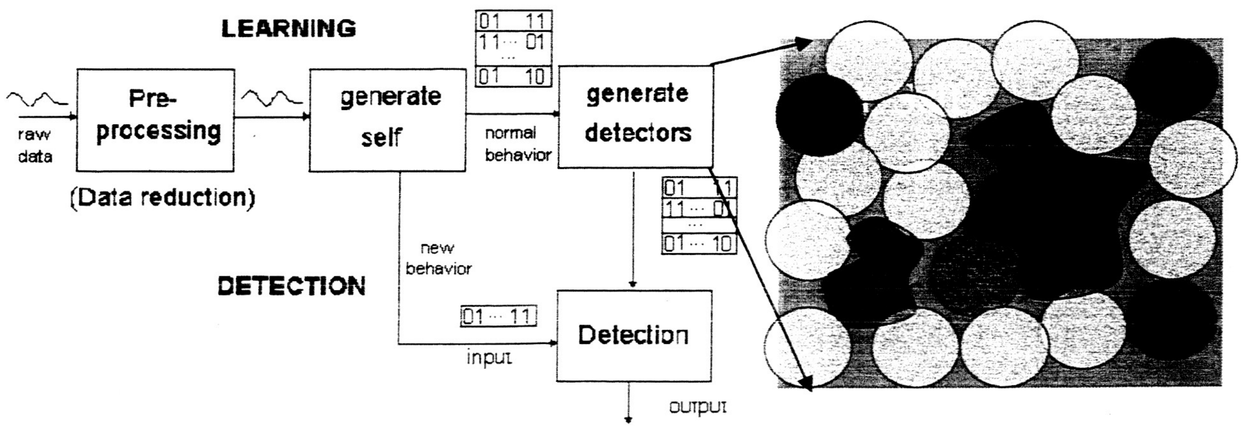

Figure 3. The concept of self and non-self space and the generation of detectors in non-self space are illustrated. Here F1, F2, etc. represent different failure conditions.

- Monitor S for changes by continually matching the detectors in R against new observations of S. If any detector ever matches, then an abnormality is known to have occurred, because the detectors are designed not to match any similar sample strings in S.

Figure 3 presents the overall concept of the AIS algorithm powered by a Real-valued Negative Selection (RNS) algorithm. The RNS algorithm uses the self/non-self space that corresponds to a subset of R^n, specifically $[0, 1]^n$. A detector is defined by an n-dimensional vector that indicates the center with varying radius; therefore, a detector can be seen as a hypersphere in R^n. Accordingly, the RNS algorithm tries to evolve a set of variable-size detectors that cover the non-self space. This is accomplished by an iterative process that updates the position of the detector driven by two goals:

- Move the detector away from self points.
- Keep the detectors separated in order to maximize the covering of non-self space.

The RNS detector generation starts with a population of initial (random) detectors, which are then matured through an iterative process. The centers of these detectors are chosen at random. The radius of a particular detector is defined in terms of Euclidian distance to its nearest neighbor in the training dataset (self sample).

Several experiments using simulated aircraft data and experimental fault data were utilized to verify the efficacy of the MILD tool [10-11].

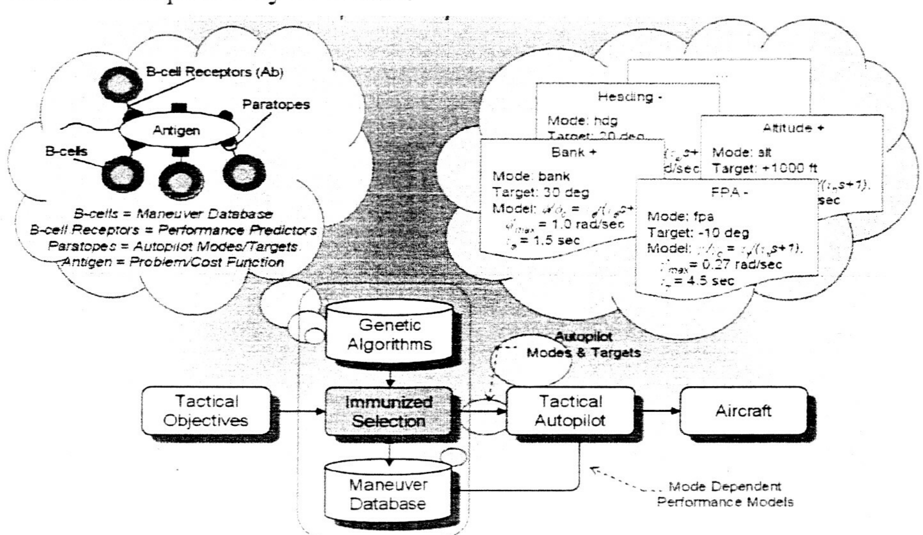

Figure 4. Immunized Maneuver Selection generates maneuver sequences to achieve strategic goals. The Tactical Maneuvering Autopilot executes maneuver sequences and provides feedback on predicted performance.

5. Intelligent Maneuvering

A tactical maneuvering system that uses an artificial immune system based approach for selecting maneuver sequences is being developed for application in aircraft maneuvering (See Figure 4). This approach combines the problem solving abilities of genetic algorithms with the memory retention characteristics of an immune system. Of significant importance here is the fact that the tactical maneuvering system can make time-critical decisions to accomplish near-term objectives within a dynamic environment. These objectives can be received from a human operator, autonomous executive, or various flight planning specialists. Simulation tests were performed using a high performance aircraft model. Results demonstrate the potential of using immunized sequence selection in order to accomplish tactical maneuvering objectives ranging from flying to a location while avoiding unforeseen obstacles, to performing relative positioning in support of close-proximity maneuvering [12].

6. Automated Design using Evolutionary Principles

Future NASA exploration missions will require advanced spacecraft architectures and hardware systems to achieve sustainability, affordability, and reliability. Critical to this goal is the need for advanced computer algorithms to manage the design complexity both for *static* design challenges on the ground (pre-launch) and *dynamic* design problems in space (post-launch). Exploration missions will require both hardware and software systems that can respond to and recover from component faults and failures and that can adapt, self-improve, self-repair, and self-reconfigure based on changing mission requirements and unexpected events.

The core technologies that are being developed at NASA Ames Research Center are based on adaptive and evolutionary algorithm methods. The methods, which include genetic algorithms, genetic programming, artificial neural networks, simulated annealing, and variants thereof, have recently begun to produce human-competitive results in real-world application domains [13]. As an example, in NASA's Space Technology 5 (ST5) mission a requirements-compliant evolved antenna was produced that is scheduled to be flown in 2005. The evolved antenna will be the first evolved hardware ever flown on a NASA mission (see Figure 5). An initial design was as good as a human-designed model and outperformed it in critical metrics such as mass and cost. A second design was evolved in less than 4 weeks after an orbit change, proof that these techniques aid designers in adapting quickly to changing requirements.

The key application areas for automated design include electromagnetics, MEMS, electronic controllers, self-repairing reconfigurable chips, and mission profile design. Some of the specific applications to be pursued in this research include antenna radiator design, reconfigurable antennas, phasing and gain circuitry optimization and design, printable antennas, phased-array antenna design, launch vehicle structure, sensors, high-precision MEMS gyroscopes, mission planning tradeoff space analysis, rapid design / re-design cycles in response to changing mission requirements, and integration of automated design/optimization methods into computer aided design tools.

In our ongoing Evolvable Systems project, we have demonstrated how a computer search algorithm based on Darwinian evolution and genetics was used to evolve an X-band antenna design currently on schedule to be on NASA's ST5 spacecraft in 2005 [13, 14]. The mission consists of three satellites that will take measurements in Earth's magnetosphere. The evolved antenna (Figure 5, top) has an unusual, organic structure and was evolved to meet a challenging set of mission requirements, notably the combination of wide beamwidth for a circularly polarized wave and wide impedance bandwidth. For comparison to traditional design techniques, we contrast the evolved antenna with a hand-designed quadrifilar helical antenna (Figure 5, bottom). The evolved antenna represents the first antenna to be fielded with an evolved design topology, and, if deployed successfully, the first evolved object to fly in space.

A second successful application of evolvable systems algorithms is in fault recovery for field-programmable gate arrays (FPGAs). A spacecraft flying through an extreme radiation environment is damaged by ionizing radiation causing a fault in one of its FPGAs. After the fault is detected, an evolutionary algorithm runs and quickly repetitively rewires the FPGA until the chip

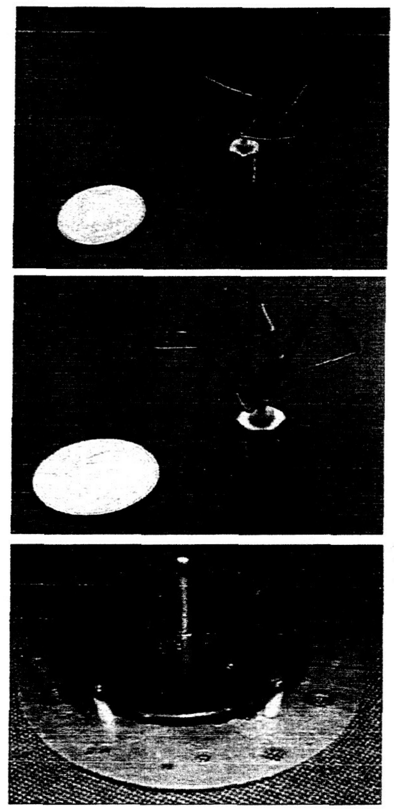

Figure 5. Evolved Antennas (top, middle) and conventionally-designed antenna (bottom) for NASA's Space Technology 5 Mission.

becomes functional again. It does this by exploiting healthy resources on the device, and sometimes even the damaged resources to regain a fully-functional chip.

7. Recommendations

Intelligent systems provide a means by which complex problems can be addressed and in many cases solved to a satisfactory level. The immediate benefits are in applications of intelligent systems to areas where existing methodologies are marginally satisfactory and incorporating intelligent systems provide better efficiencies and solutions. Examples include: inverse design, adaptive control, optimal search, etc. The future benefits are more exciting. Intelligent systems will help formulate and solve problems such as brain-like control and decision-making, human-machine collaborative work, instant speech recognition, thought-based control, human capability enhancement, advanced pattern recognition, real-time scheduling, automated design, and intelligent planning and maneuvering for exploration vehicles, and autonomous security search. On a cautious note, intelligent system researchers should examine closely the analytical framework of their innovations. Analytical framework along with standardization has been shown to be important for the ultimate ticket to real implementations in aerospace applications.

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