Autonomous Mission Planner and Supervisor (AMPS) for UAVs

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Abstract— To reduce mission manning and increase adaptability and evolvability for managing current operations of Unmanned Aerial Vehicle (UAV), Miniature Air-Launched Decoy (MALD) and future systems, an Autonomous Mission Planner and Supervisor (AMPS), based upon an Intelligent Information Agent (**I²A**) architecture for real-time, adaptive, decision making is proposed. AMPS will use a naturalistic decision-making approach to comparing sensor inputs to a priori situational "scripts" and previously collected data to improve determination/decision and execution time of appropriate actions thereby, enhancing quality and minimizing time to achieve each related mission goal. The proposed AMPS herein will describe mechanisms for employing continuous monitoring capabilities and continuously learning from multiple Unmanned Aerial Vehicles (UAVs) while coordinating activities when necessary to more rapidly and more effectively achieve mission objectives.

Keywords—Unsupervised learning, autonomous systems, mission planning

1. Introduction: Automated Mission Planning

There is an increasing need within the DoD for unmanned systems [2]. This need will only increase in the future, and, as staffing requirements are reduced, as well as the insatiable desire to minimize harm while maximizing effect, the need for autonomous or semi-autonomous vehicles will become critical. Current manual control of unmanned vehicles is manpower intensive, and as the number of manually controlled vehicles is increased, operators are quickly becoming overwhelmed. Even simplistic tasks become significant as the number of vehicles exceeds 4, with predicted number of vehicles rapidly expanding, optimal usage becomes virtually impossible when corresponding to [3]:

$$\text{vehicles} = \frac{\text{NT} + \text{IT}}{\text{IT}} = 1 + \frac{\text{NT}}{\text{IT}}, \text{NT} + \text{IT} = 1$$

Where:

NT = Neglect Time (% of time unmanned vehicle can be ignored before its performance drops to an unacceptable level.

IT = Interaction Time (% of time it takes an operator to interact with the unmanned vehicle to raise its performance to an acceptable level.

For human control of 4 unmanned vehicles, this means that each unmanned vehicle is left unattended 75% of the time. This means even simple health and status checks, along with vehicle control within varying environments is a difficult challenge. When added to already complex mission directives and varying needs for possible defensive actions, there exists a critical need for unmanned vehicles to reliably handle much, if not all of the control, status, and maintenance functions while they are in-field. Furthermore, Principles of Active Conditional Control (PACC) [19] describe that processes and complexity of control systems, as well as, numerous variations in aircraft designs, do not leave a room for maneuver: humans become a weakest link and should not be considered as an element of active conditional control approach. PACC automated monitoring of reliability in real time aircraft applications can offer 20-25% growth of mission reliability. In addition, the ability of unmanned vehicles to collaborate and cooperate on a given mission follows Network Centric Warfare [20] paradigms and increases the efficiency and adaptability of their ability to complete a given mission as a function of their shared awareness.

Many factors make the autonomous, or even semi-autonomous, control of unmanned vehicles difficult. First, unmanned vehicles, whether ground, air, or underwater, must operate in unstructured environments that are inherently unpredictable and dynamical. Second, the vehicle must have some degree of autonomous intelligence to undertake tasks without direct human involvement, especially in unstructured environments. This paper will discuss the use of an Intelligent Information Agent (I2A) framework to provide Unmanned Service Systems (USS) and Unmanned Undersea Systems (UUS) with a set of cognitive like capabilities required for semi-supervised and effective autonomous command and control [1].

One of the reasons enabling machines with "human reasoning" is so difficult is that human learning is very dynamic in nature and hence, somewhat fuzzy and random. There is no way to know when information is going to chaotically come our way, nor is it known how the information might apply to one of more simple or complex subjects, or topics in our memory pedigree [4]. Therefore, Cognitive systems like the I2A architecture, rooted in solutions conceptualized within Fuzzy Logic [4], create an environment for autonomous operations by providing a processing architecture, cognitive processes, and algorithms that facilitate human-like reasoning within the cognitive system [5]; i.e., the I2A framework's cognitive framework models human reasoning structure and provides human-like abductive reasoning methodologies. Abductive reasoning is formally defined as finding the best explanation for a set of observations or inferring cause from effect.

The I2A framework, uses a form of abduction called "Occam Abduction" which is defined as the simplest set of consistent assumptions and hypotheses, which, combined with available stored pedigree knowledge, entails adequate description/explanation for a given set of observations which has reached a previously learned threshold within the thought processes of the I2A framework cognitive framework. Figure 1 below illustrates the difference between deductive, induction, experimental, and abductive reasoning. Abduction consists of computing explanations (hypotheses) from observations. It is a form of non-monotonic reasoning and provides explanations that are consistent with a current state of knowledge and can become consistent or inconsistent, as new information is gathered [6].

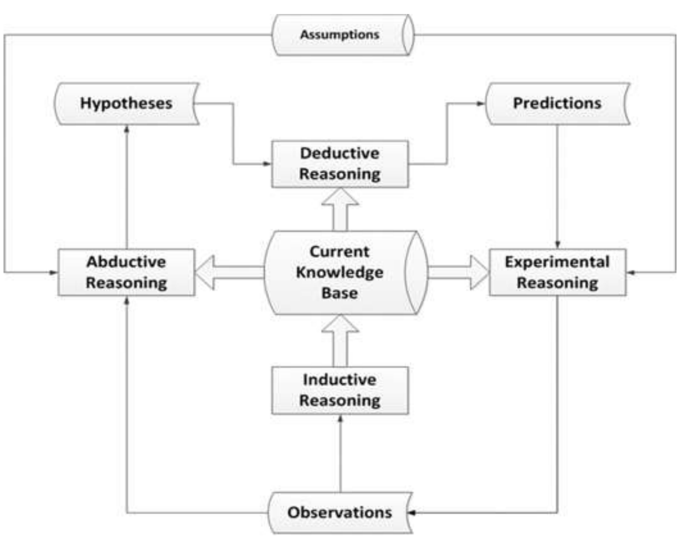

Figure 1 – Differences Between Reasoning Systems

Human neuroscience research shows that generating new knowledge is accomplished via natural means: mental insights, scientific inquiry process, sensing, actions, and experiences, as well determining the context of this newly acquired knowledge, which characterizes the knowledge and gives it meaning [6]. Truly autonomous systems must contain these same processes and abilities. True learning can be a lengthy iterative process of knowledge discovery, experience, and refinement as new information is attained. This recursive refinement of knowledge and context occurs as an autonomous vehicles cognitive system interacts, over period, with their environment; where the granularity of information content results is analyzed, followed by the formation of relationships and related dependencies.

Occam Simplicity Through Orthogonality

Discovering optimized Occam like simplicity within any design has been vigorously researched within mechanical engineering complexity theory and axiomatic design [21]. Two core axioms: Independence Axiom and Information Axiom, when applied to I2A Framework, provide solutions for optimizing Occam simplicity and orthogonality. The objective of the Independence Axiom is to initially drive any information context into their core precepts/concepts minimizing overlap and maximizing understanding. Secondly, the Information Axiom's objective is to focus upon minimizing information content within any given context, thereby, removing frivolous, non-core topic-applicable content. The Human Brain's prefrontal cortex performs these operations naturally. When embedding Occam Abduction based axioms into I2A Framework we applied them to cognitive functional requirements and therefore support driving to optimal I2A Framework design.

Ultimately, knowledge is attained from assimilating the information content until it reaches a threshold of decreased ambiguity and level of understanding, and is then categorized by the brain as knowledge, which acts as a catalyst for decision-making, subsequently followed by actionable activity or the realization that a given objective or inference has been attained [7]. Any functioning and evolving, autonomous, artificially intelligent system must have a cognitive system to perform similar activities. Here we present an overview of the Autonomous Mission Planner and Supervisor (AMPS) required to provide autonomous/semi-autonomous vehicle control.

To reduce manning and increase adaptability and evolvability for current unmanned systems an Autonomous Mission Planner and Supervisor (AMPS) based on an Intelligent Information Agent (**I²A**) architecture for real-time, adaptive, decision making is proposed [8]. The AMPS will use a naturalistic decision-making approach to comparing sensor inputs to a priori situational "scripts" and previously collected data to determine and execute appropriate actions per the current mission goals. AMPS performs continuous monitoring and continuously learning from multiple Unmanned Aerial Vehicles (UAVs) and coordinates their activities, as appropriate.

2. AMPS BASIC ARCHITECTURE

The Automated Mission Planner and Supervisor (AMPS) will control and monitor multiple Unmanned Aerial Vehicles (UAVs) thus reducing the manpower, while providing improved adaptability required to operate these systems. The functionality of the AMPS is focused in three main areas:

1. The control and monitoring of UAVs based on the current mission goals and the information stored about previous missions (memories). Here, the overall mission objectives are monitored and rated, based on lessons-learned from previous missions and how to apply them to the current mission objectives.
2. The ability to learn and modify its behavior based on data obtained during the execution of a mission and by monitoring operator actions. This includes participating in post-mission briefings during which the operator can explain the actions they took and the AMPS indicating possible areas of operational improvement
3. Performing prognostic health management for the UAVs it monitors to improve maintenance efficiency and reduce downtime.

The AMPS is based on a multiple Intelligent Information Agent (**I²A**) architecture originally developed under the Colorado Engineering, Inc. (CEI) AFRL program: Learning Agents for Autonomous Space Asset Management (LAASAM). This architecture processes inputs (UAV sensor data, operator actions, mission goals) and uses the processed inputs to retrieve the appropriate situational "script" to control the actions of the UAVs under its control. The system also uses the inputs to improve and adapt the scripts. The AMPS also maintain, updates, and predicts the state of the UAVs to determine when maintenance should be performed to prevent UAV failure and reduce downtime.

The AMPS will itself be supervised by a human operator who will monitor and/or approve certain actions (modifying a mission goal based on inputs and situational awareness, authorizing a UAV to launch a missile, etc.). As the AMPS is capable of supervising multiple UAVs the number of operators required per UAV or UAV constellation will be reduced. The role of the operator will be more of a supervising decision maker with the AMPS handling the more mundane/repetitive tasks associated with UAV operation. By relieving the operator of these tasks, the physical and mental workload is reduced, and the human can focus on assuring that the mission is accomplished [9].

Features of the solution are described below:

Memory and Learning. The AMPS will store and retrieve and continuously learn from information based on previously executed missions. At first this information can be loaded into the system to provide initial "memories" for use. As more missions are performed the AMPS will add information that will modify these scripts. Scripts that lead to the satisfaction of mission goals will be reinforced while those that interfere with mission success will have their weighting reduced.

Reinforcement learning is accomplished via a combination of biologically inspired components known as Knowledge Relativity Threads [22,23] which provide continuous context learning constructs within memories and concepts of Noology [24] which supports rapid effective causal learning capability development over time.

This approach alleviates the problem of realizing a time-varying mapping of neural structures, commonly referred to as the sequential learning problem. Neural-based systems tend to forget previously learned neural mappings quickly when exposed to new types of data environments, a phenomenon known as "Catastrophic Interference" (CI). The neural elements of the AMPS will use the scripts to retain learned data and eliminate Catastrophic Interference [10].

Flexibility. The AMPS will provide flexibility in several different dimensions. The first dimension is the ability to interact with and control a variable number of UAVs. This capability is predicated by the reality that different missions will start or end at different times. The second dimension is the ability to apply one or more sets of mission goals to the UAVs being controlled by AMPS. The third dimension is the capability to incorporate and apply new configurations, such as changes to mission goals, and informational awareness scenarios and information to support decision making in real-time situations.

Robustness. The information and control are distributed with the AMPS architecture; thus, the system can degrade gracefully, even when some of the elements are out of service temporarily. This provides the advantage of having the AMPS continue the mission in a degraded fashion or to devote the reduced resources to a subset of the UAVs it is controlling while having the human monitor assume control of one of the vehicles to continue its mission or to return it to base. This will reduce the load on the AMPS until the problem is resolved and the system is returned to full functionality.

Prognostics. The AMPS will have a health management system to maintain its own performance and that of the UAVs it controls. The AMPS prognostic health management [12] capability is based on the ability to:

1. Accurately predict the onset of impending faults/failures or remaining useful life of critical components
2. Quickly and efficiently isolate the root cause of failures once failure effects have been observed. In this sense, if fault/failure predictions can be made, the allocation of replacement parts or refurbishment actions can be scheduled in an optimal fashion to reduce the overall operational and maintenance logistic footprints.

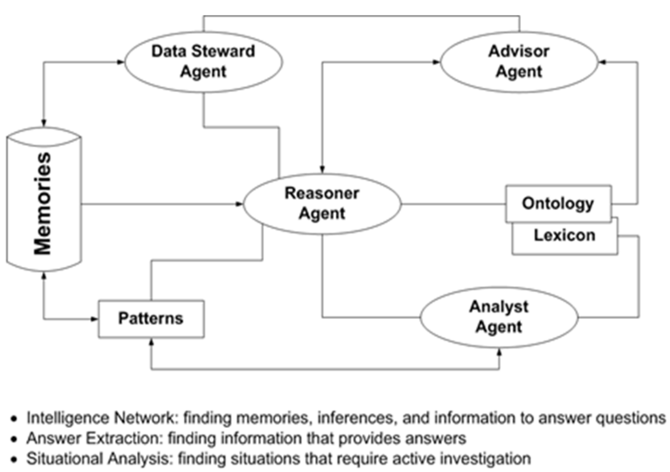

Figure 2. The I^2A AMPS Cognitive Architecture

From the fault isolation perspective, maximizing system availability and minimizing downtime through more efficient troubleshooting efforts is the primary objective.

AMPS will be incrementally developed to create a system that will autonomously manage the overall monitoring, fusion, and analysis of incoming data/information [13] for UAVs. Development and verification of the Intelligent Information Agents (**I^2As**) and information management techniques will be the first area of focus. The architecture will support fusion of disparate, dissimilar, incomplete, and noisy data, obtained from multiple information sources and types. The second development step will be to develop and test the algorithms that will establish information collection criteria, plans, and tasks, and then execute and monitor progress to ensure mission goals are satisfied. The information collection and analysis process are tuned based on feedback from sensors and human operators to satisfy processing and decision-making needs.

Designs for the various **I^2As** and information management algorithms will be created to experiment and demonstrate the researched methodologies and techniques. These will be combined to produce a design, system requirement and software requirement specifications, and a report describing the effectiveness of the information agents to automate the AMPS activities. Any autonomous information processing and situational awareness agent-based system must consider overall real-time performance issues. It should have the capability to overcome inherent bottlenecks that result from massive volumes of data being generated by the collection sensors or processors transforming the data into information and knowledge. A collection management system must can stay on top of the sensors and intelligence inputs that drive collection [14]. Figure 2 illustrates the **I^2A** basic architecture

Simulated human decision making has applications across a broad spectrum of human commercial activities and man and machine interfaces. A system in which the machine can make sound decisions more effectively than a representative sample of human practitioners can reduce manpower costs, increase decision timeliness and in some applications, reduce risk to humans. Building upon the technologies, architectures, and prototypes developed under this fundamental research effort, CEI is researching and developing an overall prototype system that combines all elements of this research into the Autonomous Mission

Planning and Supervisor (AMPS). Potential applications and markets include activities where the human operator is removed or isolated from the environment that the machines or sensors are operating in: constrained by the lack of timely communications and sensory inputs. We intend to apply the technology as broadly as possible once a reliable approach is proven.

3. Human-System Collaboration

The purpose of autonomous unmanned systems is presumably to provide some type of services on behalf of humans. Hence, to help define optimal human-AMPS interactions, we must look to the characteristics of human interactive behavior. Human collaboration, with other humans, fundamentally comprises trust and knowledge of another's abilities and limitations. In short, it's not possible to have an interaction between two human entities without there being some level of expectation of the interaction [14]. Let's consider a simpler example of human interaction with animals. Humans, for example, cannot completely predict an animal's behavior. However, it is still important to know how the animal will typically behave in order to predict and plan for the proper interactive response (e.g. give food, play, run to safety). Again, it comes down to human expectations. Understanding the animal's abilities and limitations will reduce frustrations of trying to meet a goal. (e.g. taming a lion) Knowing the abilities of the animal changes our expectations. Bulldogs can't swim because of the shape of their nose, similar for dogs with large chest. Humans can accommodate for these limitations when they know about them. Understanding the expectations, abilities, and limitations of a UAS/UAV as well as the cognitively designed understanding of UAS/UAV expectations, abilities, and limitations of humans, is vital to efficient, and useful collaboration. Collaboration is much more than a mere working relationship. It is both a process and an outcome. The process is a coming together to work on a common problem while understanding that each other has influence on the other. The collaborative outcome is a solution where all parties can agree on the final solution [15]. Typically, collaboration happens because an individual cannot accomplish the same goal alone. It is more than an association relationship it is more like a partnership.

Current human-autonomous system interaction technology and design has developed from master-slave type interactions toward more collaborative. Karami, Jeanpierre, and Mouaddib [16], described a model where the autonomous system can consider human intentions and operate without communication. Karami, et al., also discussed how autonomous systems can build beliefs about human intentions by observing, collecting, and perceiving human behavior. Although the experiment shown was a seemingly simple task of moving objects, the results showed further promise for human-UAS/UAV collaboration much more advanced than in the previous master-slave paradigm.

Many existing Unmanned Vehicles, intelligence information processing systems, cyber monitoring and security systems, all continue to have the "human-in-the-loop" making ultimate decisions but are making strides toward autonomous operations every day. However, these systems are all developed with the goal of thinking all the possible causalities processed by the infamous IF, THEN statements that the best software engineers can devise to prepare each of these systems for what it might someday encounter. Therefore, to evolve beyond this paradigm, we propose a cognitive system (i.e., the **I^2A** framework) comprising the following capabilities in order to allow even limited autonomy and collaboration between unmanned vehicles:

Cue Familiarity: cue familiarity is the ability of the system to evaluate its ability to answer a question *before* trying to answer it [17]. In cue familiarity, the question (cue) and not the actual memory (target) become crucial for making cognitive judgments. This implies that judgments regarding cognitive processing and decisions would be based on the system's level of familiarity with the information provided in the cue. This executive-level, top-down cognitive judgment requires abilities that allow a UAS to judge whether the answer to a question is known, or whether the system is already familiar with the topic or mission, allowing the system to judge unfamiliar terms or conditions.

Cognitive Accessibility: suggests that a system's memory will be more accurate and more rapidly available for use when the ease of cognitive processing (accessibility) is correlated with memories. For our UAS/UAV, we propose that the quality of information retrieval depends on the system's density of knowledge on the topic or subject or individual elements of informational content about a topic. Individual elements of topical information can differ in strength while the speed of access is tied to both density of knowledge and level of memory when a system responds to the information cues.

Cognitive Competition: comprises three principles:

- The UAS/UAV cognitive processing system (its brain) is activated by a variety of inputs (sensors), perceiving a variety of sensory inputs. Hence, different types of information are sensed simultaneously.
- Competition develops over time as simultaneous data is processed within the multiple cognitive processing subsystems and is adjudicated by the **I^{2}A**s.
- Competition is assessed utilizing top-down neural priming.[1]

Cognitive Interaction: Combines cue familiarity and cognitive accessibility. In cognitive interaction, once cue familiarity fails to provide enough information to make cognitive inferences, cognitive accessibility accesses extended memories and may employ stored memory cues to access additional information to attempt to make the required cognitive inferences. This may result in slower response time that with cue familiarity alone. Even in humans, reaction times can be slower when the situation requires additional learning [18].

4. Conclusions and Discussion

Having the AI system assist in the planning and supervision of UAV/UAS systems will become an ever-increasing need as the proliferation of UAS/UAV fleets increases over the next decade. To "learn" that basics of system management, we feel it will be necessary for human-AI interaction in the form of Human Mentored Software (HMS), where the human helps "teach" the **I^{2}A** system how to do its job. This system, called the Cognitive, Interactive Training Environment (CITE) facilitates HMS is shown in Figure 3 and will allow the system to learn from humans, including the heuristics required for ad-hoc mission planning and supervising.

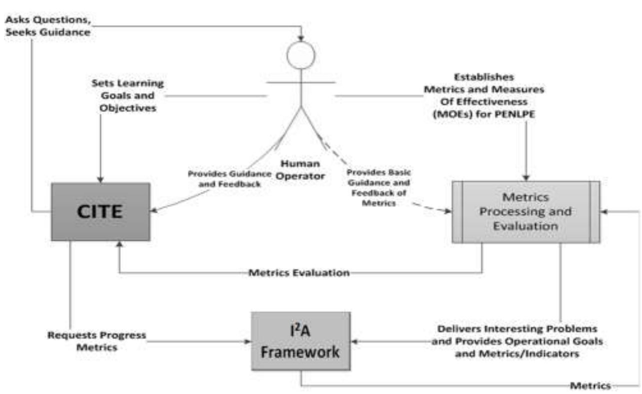

Figure 3 – the CITE High-Level Architecture

Here we have presented a high-level view of the AMPS system. The next step is to instantiate the **I^{2}A** system and use it in a test scenario with a model of a UAV fleet.

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[1]Priming is an implicit memory effect in which exposure to a stimulus influences a response to a later stimulus. It can occur following perceptual, semantic, or conceptual stimulus repetition. The effects of priming can be very salient and long lasting, even more so than simple recognition memory

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