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"Levels of Autonomy: Command and Control of Hybrid Forces"

Topic 3: Towards Internet of Intelligent Things in Highly Connected Battlefield

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Levels of Autonomy: Command and Control of Hybrid Forces

Complex operations, in which human units seamlessly collaborate with machines, have never been so close to becoming a reality. The enabling technology is mostly ready, but the Command and Control (C2) infrastructure remains a major roadblock. Collaboration involving Hybrid Teams demands new ways of dealing with levels of autonomy to ensure operational efficacy and efficiency. In this paper we describe a new approach for Autonomy that enables Hybrid Teams to collaborate to achieve mission goals within the Internet of Intelligent Things (IoIT).

We define a Hybrid Team as composed of biological, mechanical or cybernetic agents. We understand C2 as a process that encompasses building collaboration to achieve goals. Rather than focusing on the "platform" we focus on their cognitive dimensions. We have developed a framework, Hybrid Cognitive Collaboration (HyCCo), to model C2 in this domain. We define Autonomy as the ability of a Cognitive Agent (or Hybrid Team) to generate a response to environment changes and to preserve a goal commitment. The Levels of Autonomy are then defined as the degrees of freedom a Cognitive Agent has when executing those responses.

We model HyCCo as a collection of operational processes to be executed by Cognitive Agents depending upon their capabilities. The intent of HyCCo is to provide minimum requirements for the C2 of Hybrid Teams. In this paper we present a number of use cases for the HyCCo framework. The main scientific benefit is the establishment of a new framework for autonomy for both current operations and future generation systems development.

Keywords: Collaboration, Autonomy, Cognition, Human-Machine Interaction

1) Introduction

In complex operational situations, such as Disaster Relief, Humanitarian Aid, Peacekeeping and Conflict, the people involved face many challenges and demands on their time. Individuals, teams and organizations must formulate and execute missions in a complex environment. We see the development of the Internet of Intelligent Things (IOIT) (Arsenio et al., 2014) as a key enabler for such missions in the future. Having "pervasive robotics" available raises the issue of autonomy and collaboration within the IOIT.

Even when we send people to face the unknown, we still expect them to behave according to some principles and criteria. Those constraints are given through education, training, expressed intentions and self-protection instincts. It means that we expect them to act as reasoners, using their Cognition to solve problems by exploring the environment and adapting their comprehension of the world. In this perspective, cognition is the main asset to preserve adaptability in achieving a mission in an uncertain environment.

Cognition itself is not directly related to specific missions or goals. Those are given as parameters for the reasoner to search in different problem spaces for possible courses of action. The problem space, by the same argument, is also a parameter for the reasoner to delineate courses of action, by constricting or spreading a search through this space.

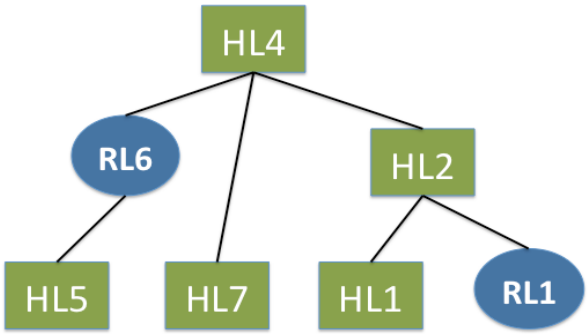

Figure 1 - Human Machine Teaming

In the future, our dependency on machines for performing missions will tend to increase, as we develop the IOIT. One of the major factors is the ability to save or preserve human lives in dangerous circumstances. Another factor is economic, in that it is less expensive to build unmanned entities, as they are not required to have the same standard of survivability as humans. It means that the price of an unmanned entity is directly related to its operational capabilities. Furthermore, there is experience in the last two decades of the operational value of unmanned vehicles.

As the introduction of machines in operational missions gives new possibilities, it also poses some important questions concerning security and trust (Sycara and Lewis, 2004). The use of semi-autonomous entities increases trust for unmanned vehicles, but it comes with the price of assigning a human operator to directly control a single vehicle. By following the current tendency, we may need hundreds of pilots for a relatively inexpensive group of Unmanned Aerial Vehicles (UAVs). This approach does not scale, because of human cognition performance limits. As the number of controlled vehicles increases, so does the emotional stress and the potential for wrong assessments and decisions.

For those reasons, we need to face the problem of building effective collaboration between humans and machines for future operational missions. In other words, the machines need to be more autonomous and need to collaborate with Humans for the effectiveness of missions (Dunin-Keplicz & Verbrugge, 2011). We envision future hybrid "teams" consisting of machines working under human control, but also humans working for machines to achieve a mission as seen in Figure 1, which is a task organization. The numbers in Figure 1 indicate more or less autonomy (thus HL7 is a human with a high level of decision making authority, RL1 is a robotic entity with a low level of decision making authority). Note that in our framework, we can have an entity with high autonomy (H7) working for an entity with a lower autonomy (H4). Such a hybrid organization raises interesting research questions concerning trust and effectiveness.

We see humans and machines as having complementary capabilities, as shown in Table 1. In the table, glucose level refers to the energy necessary for humans to perform at an optimum level, which corresponds to a machine's (or robot's) need for electricity. As machines increase in capabilities (such as self driving automobiles), we expect to see more "teamings" with humans that have a significant amount of collaboration, in addition to interaction. We also expect to see machines as part of much larger teams, or multiteams in the future (Zaccaro, Marks & DeChurch, 2013).

As we must leverage the autonomy of machines, robots, unmanned platforms and software agents in forthcoming operations, we see some new questions emerging about how decision rights are distributed. Decision rights are the specification of who can make decisions (such as Rules of Engagement). More than that, the dynamics of future operations may require dynamic decision rights distribution, causing flexible and dynamic implementations of autonomy through an organization.

Table 1 – Complementary Capabilities between Man and Machine

	Human	Machine
Sensing	• Medium glucose level • Multi Dimensions	• Intermittent Electric Power • Low Latency
Abstraction	• High glucose level • Self Organizing	• Continuous Electric Power • Algorithmic
Calculation	• High glucose level • Estimation	• Continuous Electric Power • High Speed
Pattern Discovery	• Medium glucose level • Self Organizing	• Continuous Electric Power • Algorithmic

Humans and Machines must be able to dialogue and to commit to each other in a Collaboration. Those properties are essential for the workload distribution, synchronization and adaptation in the operational scenario. For this reason, we need to properly characterize the collaboration environment that will be the main focus of this research.

But, in this research, we restrict ourselves to a cognitive collaboration. First of all, we are not going to describe every possible collaboration between Humans and Machines that may take place in the future. We are expecting to describe the collaboration that empowers the Humans with advanced cognitive capabilities.

For that reason, we model Humans and Machines in a mission space using the same conceptual model. We believe in the assumption that a cognitive collaboration enables any set of Agents to build many other types of different operational collaborations. From now on we denote, in the operational scenario, humans and machines as cognitive agents. The cognitive agent has one motivation: to collaborate in the operational scenario to achieve goals**.**

We believe that our concept of autonomy maps into the mission space of Complex Endeavors (Alberts and Hayes, 2007) and could be used to develop protocols and interfaces for future C2 acquisitions. The HyCCo framework is also designed to take advantage of differing autonomies in the IOIT. We also believe that the current notions of autonomy are too restricted, in not considering the more complex problem of hybrid teams, and of propagating decision rights through teams. Our framework is oriented at a cognitive level, rather than a performance level. In the next sections, we examine autonomy in “mixed” teams in detail, and define the HyCCo Framework. We end with an experimentation plan to assess the HyCCo framework through simulation.

2) Related Work

There is a large literature on autonomy for unmanned vehicles. In this section we review the two most common autonomy frameworks and then survey research related to how humans can team with robotic or software entities in a mission context.

2.1) Autonomy Levels for Unmanned Systems (ALFUS) Framework

The most referenced work on autonomy for unmanned systems is the Autonomy Levels For Unmanned Systems (ALFUS) framework [Huang et al., 2005]. The ALFUS is not a specific test or metric, but rather a model of how several different test metrics could be combined to generate an autonomy level. The main focus of this framework is to determine a single value of autonomy for a single unmanned system. In the ALFUS framework, sets of variables are organized in three dimensions, namely: Mission Complexity, Environmental Difficulty and Human Interface.

The detailed autonomy level model implementation is for accurately assessing the autonomy level of a UMS. It uses the three axis method of the Contextual Autonomous Capability (CAC). Each axis refers to a metric group (mission complexity, environmental complexity or human independence). These axes comprise scores from bench tests. For a given mission and environment, metrics are measured for the mission complexity, environmental complexity, and human independence of the UMS, and these metrics are combined to form a level of autonomy. It consists of a 0 to 10 numeric scale that characterizes the autonomy level of a given UMS.

It is necessary to assess many points in this three-dimensional space to be able to evaluate an autonomy level in the ALFUS framework, by producing a surface of evaluations. As each evaluation demands the use of the unmanned system in a specific environment to accomplish a specific mission (along with any human interaction), there is a high evaluation cost. As demanded by the Testing and Evaluation community, there was a need for a single value to summarize the evaluation rather than a very complex model. For this reason, the framework was offers a scale of autonomy levels from 0-10.

Even though the ALFUS provides a scale for autonomy levels evaluation, the combination of the measurements in many points demands specialized knowledge and assessment, which bring a measure of subjectivity to the overall result. Viewed with this perspective, the ALFUS scale is more of an approximation of the intended autonomy levels.

2.2) Non-Contextual Autonomy Potential (NCAP) Framework

The Non-Contextual Autonomy Potential (NCAP) framework provides a way to measure autonomy for the Evaluation & Test community. Rather than analyze performance data, the framework uses “Potential” capabilities. The NCAP framework relies upon a high-level model of intelligent Unmanned Systems (UMS). Because execution is implicit in all UMS, regardless of autonomy level, a UMS’s AL is defined by the architecture level at which a human interacts with the robot. The NCAP defines four autonomy levels. The levels range from 0, fully non-autonomous, to 3, fully autonomous. A UMS’s autonomy level is defined within the context of a generic architecture model.

The NCAP framework considers the components of a high-level architecture to determinate the autonomy level of a given UMS. The autonomy level then corresponds to the component which requires human intervention in the sequence: Perception, Modeling, Planning and Execution. The key difference between the NCAP's approach and previous methods for defining UMS autonomy level is that the NCAP treats autonomy level and autonomous performance separately.

By this perspective, the components of the UMS model are also seen as stages of a process and the autonomy levels are subsequences of that process. As the subsequences may include others, there is a natural ordering for the autonomy levels definition. On the other hand, it requires the UMS to be able to autonomously perform those predefined subsequences.

By avoiding the UMS performance assessment as part of the autonomy level evaluation, the NCAP is much simpler than other autonomy frameworks (e.g. the ALFUS framework), but as mentioned by Durst et al. (2013) it still lacks mathematical modeling to provide a single value for autonomy levels evaluation.

2.3) Research on Human/Machine Mission Teams

There is a large and growing literature on autonomy pertaining to robotic entities. Beer, Fisk, and Rogers (2014) give an exhaustive survey of different ways to measure autonomy for robots, and present a "Levels of Robot Autonomy" framework, but it is oriented towards a single entity, rather than a hybrid team, and is task dependent.

Alnajar, Nijhuis, and Visser (2010) describe coordinated action in a heterogeneous rescue team. The team is composed of an AirRobot and a ground robot working together in a search and rescue domain, but is not interacting with a human.

Landen, Heintz, and Doherty (2012) investigate developing principled mixed-initiative interaction between UAV's and human operators by designing a distributed heuristic search algorithm for allocating the individual tasks in a mission representation to individual platforms. Planning is certainly a critical part of performing missions with a hybrid team, but needs to be done with an awareness of the cognitive capabilities of machines.

In general, there are very few cases where researchers have examined autonomy in large teams that have complex C2 relationships in a mission context. There are many excellent case studies of humans performing missions using robotic entities, but very few that look at how a cognitive collaboration might be designed.

3) HyCCo Framework

We expect in the future a large number of autonomous entities to collaborate with Humans to accomplish operational missions. The escalating number poses some serious questions upon the engineering of any engineering approach to build a successful collaboration between Humans and Machines.

In the Human body, there are trillions of cells working together for the benefit of the whole body, each organ, each tissue and every cell. There are two important categories of processes running in the Human body: Homeostasis and Immune defense. The Homeostasis is designed to preserve some properties, like the temperature, between an interval of healthy values. The emerging property is *Organization Stability* of the Human body. The Immune defense is designed to add resilience to the Organism. It brings the Organism back to the dynamic equilibrium the Homeostasis is responsible to maintain.

"*The human organism consists of trillions of cells working together for the maintenance of the entire organism. While cells may perform very different functions, the cells are quite similar in their metabolic requirements. Maintaining a constant internal environment with everything that the cells need to survive (oxygen, glucose, mineral ions, waste removal, etc.) is necessary for the well-being of individual cells and the well-being of the entire body. The varied processes by which the body regulates its internal environment are collectively referred to as homeostasis.*

Homeostasis is the tendency of a system, esp. the physiological system of higher animals, to maintain internal stability, owing to the coordinated response of its parts to any situation or stimulus tending to disturb its normal condition or function." (Boundless, 2016)

According to Boundless (2016), the Homeostatic Process involves three mechanisms:

1. **Receptor**: percepts environmental stimuli;
2. **Control** or **Integrator Center**: process the information from the Perception;
3. **Effector**: responds to the commands of the Reasoning by either opposing or enhancing the stimulus.

The Immune defense is responsible to produce the Response of the Organism to any kind of threat, from offending bacteria to psychological disorders. For that purpose, the Immune defense uses the same kind of mechanisms as the Homeostasis, but it adds a very important mechanism to the agility, the efficiency and efficacy: the *Memory*. The *Memory* contains all the known Responses to the same kind of offense.

The Homeostasis Process is designed to maintain some conditions, e.g. the body temperature around 36.5 degrees Celsius, and the Immune defense process is designed to recover some conditions, e.g. no bacteria infection. Both types of processes encompass the notion of objectives and, therefore, the notion of Goals. We designate those process as Response Processes.

Definition 3.1: The Response Process is a Homeostatic Process to accomplish a set of Goals in the Operational Scenario. The Response Process is composed by Response Phases:

1. **Response Demand**;
2. **Response Production**;
3. **Response Selection**.

In the Response Demand (RD) phase, the need for a Response is identified based on the perception of the environment. The Response Production (RP) is the phase Responses are searched and evaluated. In the Response Selection (RS), based on some criteria, some Response is selected. It means that the Response Process is an information processing mechanism designed to run over informational systems.

An analogy can be made to a military unit. An RD would be performed by a sensor or a soldier, taking in data and processing it to develop Level 1 or Level 2 Situation Awareness (Endsley, 1995). An RP would be performed by a staff, preparing options and plans for a mission. And an RS would correspond to a military commander, who is making the decisions, but does not necessarily perform information fusion or detailed planning.

Definition 3.2: A **Cognitive Agent** (CA) is any System with the architecture in Figure 2.

The Perception subsystem may add to or update Information in the Memory. The Reasoning subsystem demands Information from the Memory to be able to do reasoning. It adds, updates and remove entries in the Memory. The Execution subsystem depends on Information to act in physical, informational and collaboration environments. It also stores in the Memory a

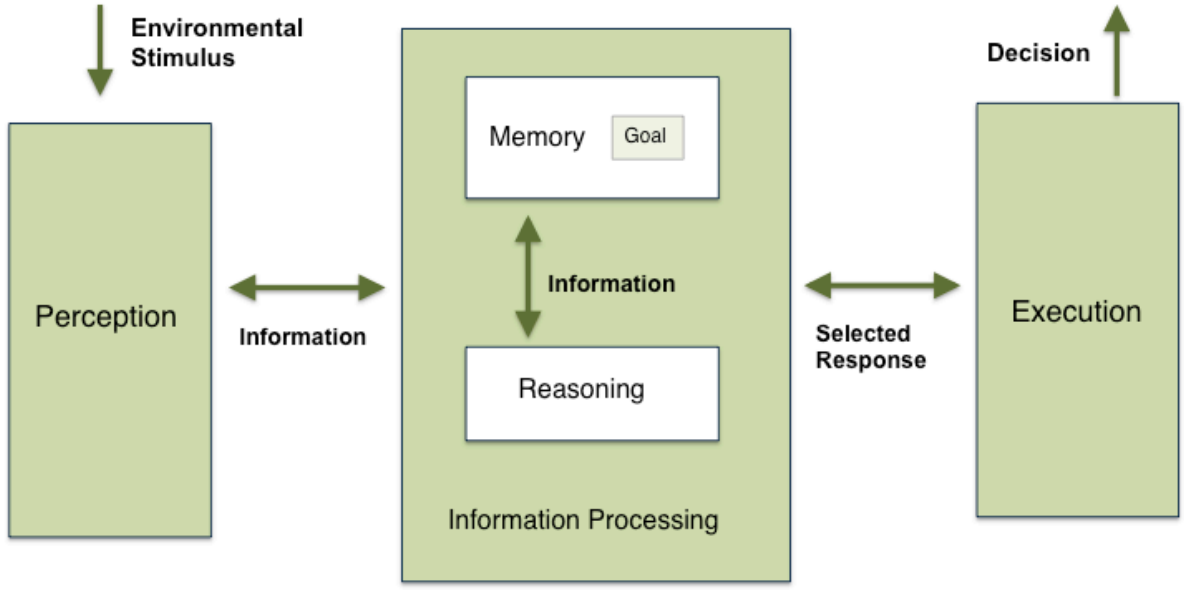

Figure 2: Cognitive Agent Architecture

performance history. Every subsystem uses the information in the memory at least for configuration. See the more detailed cognitive architecture in Anshakov and Gergely (2010) for more details

The subsystems of a Cognitive Agent may be composed by many Cognitive Agents. It means that the Cognitive Agent Architecture may repeat itself inside the subsystems. On the other hand, each of the subsystems may be a distributed system. In any case, we want the Cognitive Agents to collaborate in the mission space. As the subsystems may be composed by smaller Cognitive Agents, it means, by the definition of Cognitive Agent, that there may be many different instances of Response Processes running at different level. This behavior is very similar to the Command and Control Processes in the mission space. Many Cognitive Agents may participate on different Response Processes. But, as a consequence of specialization, limited freedom may be given for them to collaborate. In many complex missions, limited autonomy (through distribution of decision rights) is given to Humans and Machines.

Definition 3.3: **Autonomy** is the freedom a Cognitive Agent has to control a Response Process.

Definition 3.4: The Response Demand Autonomy is the freedom to perform Response Demand. By analogy, we define Response Production Autonomy and Response Selection Autonomy. The RD-Autonomy, RP-Autonomy and the RS-Autonomy will be called as **Autonomy Levels**.

Definition 3.5: The Response Demand Behaviors is the freedom on how to perform Response Demand phase. We denote it by RD-Behaviors. By analogy, we define RP-Behaviors and RS-Behaviors. The RD-Behaviors, RP-Behaviors and the RS-Behaviors will be called as Operational Behaviors.

The Autonomy Levels and the Operational Behaviors are given by Decision Rights Distribution.

Definition 3.6: **Decision Rights Distribution** (DRD) is the process to establish, control and change Autonomy Levels and Operational Behaviors in the Mission Space.

The Decision Rights Distribution is restricted to a set Agents and the ranges of allowed Autonomy Levels and Operational Behaviors. Those ranges may be given by:

- The Mission Space;
- High level behavioral constraints, such as Rules of Engagement;
- Organization configurations, with roles and task distribution;
- Goal definitions.

The DRD may positively indicate the expected behaviors or negatively indicate the undesired behaviors. By constraining the Operational Behaviors, it reduces the complexity of the Response Process, but it also reduces flexibility. The equilibrium between those aspects, complexity and flexibility, depend on the mission space.

Definition 3.7: We define the Autonomy Level **AL** as determined by the formula:

- **AL = RD + 2*RP + 4*RS**

RD denotes RD-Autonomy and similarly for RP and RS.

It means that for the measurement of autonomy levels, we have designed RS to be much more important than RD. It also means that having RD and RP does not equal having RS. An example of this situation occurs, in a mission, when a commander cannot verify any need for change in an Operational Plan and, therefore, trusts its staff to perform RD and RP phases. The measurement of the Operational Autonomy of the commander is higher than its Chief-Of-Staff, because only the commander has freedom to perform Response Selection. Table 2 shows the different levels of autonomy possible in the HyCCo framework.

In Table 2 we define 7 levels of autonomy, ranging from the ability to report on a perception of the environment (level 1) to being able to decide on an action (levels 4-7). An entity with autonomy level 1 could be a simple sensor that is reporting a reading that reaches a threshold. An entity with autonomy level 2 could contain a process that prepares plans to respond to certain situations. An entity with autonomy level 4 is capable of deciding which plan to perform. The other autonomy levels are combinations of these three levels corresponding to RS, RD and RP.

Table 2

Level	0	1	2	3	4	5	6	7
Response Demand (RD)		■		■		■		■
Response Production (RP)			■	■			■	■
Response Selection (RS)					■	■	■	■

Whenever a Cognitive Agent has an autonomy level, it also has the autonomy levels that corresponds to each of the Response Phases it has freedom to perform. For example, if a CA has autonomy level 5, it also has autonomy level 4 and autonomy level 1, but no autonomy level 2.

Figure 3 shows the possible responses, RD, RP and RS running in the Cognitive Agent architecture. In this figure, we have shown a communications mechanism that receives DDR information as well as inputs and outputs from the response processes.

For an agent with autonomy level 1, information comes in from the environment (ES), and is processed into RD output information that can be sent to another agent for planning or decision. Such an agent could be a sensor or a human with low autonomy.

For an agent with autonomy level 2, information would come in as RD information, already processed, and the agent would then generate decision or plan options. This would be output as

RP information. Such an agent could be a command staff (considered collectively) or a software planning program.

For an agent with autonomy level 4, information would come in as RP information, and the agent would decide which option to execute. This would be output as a decision. Such an agent could be a commander.

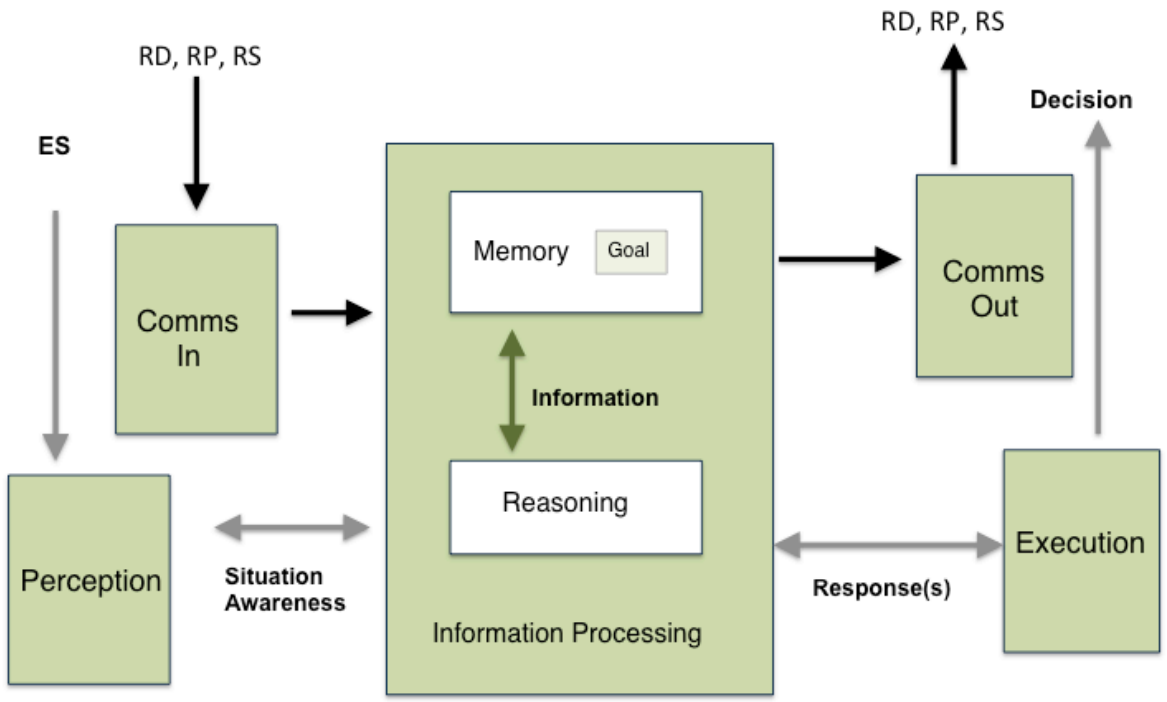

Figure 3 – Cognitive Agent Responses

While we have created additional autonomy levels that mix these responses (autonomy levels 3, 5, 6 and 7), only autonomy levels 7 has a clear interpretation, which would be an agent that is fully capable of sensing, planning and making decisions.

In the HyCCo framework, there will also be a number of response processes running for any particular agent. Two such processes common to most agents would be 1) Self-preservation; and 2) Accomplish the Mission given. For each process, different autonomy levels can be set. An example would be an organization that has only a few highly capable decision makers, but a large number of sensors and agents capable of limited processing abilities. The self-preservation autonomy levels may be set quite differently for the machine agents involved, as opposed to the human agents in the mission.

Another important aspect regarding the Cognitive Agent implementation is its ability to reason under uncertainty. As the autonomy level of a Cognitive Agent increases, so does the size and complexity of the decision space it has to deal with. For instance, the number of conflicting goals

and their associated weights that must be included in the agent's utility function make it very hard to implement an effective Cognitive Agent, especially within the time constrains involved in most of the agent's decisions. For example, an agent with limited autonomy might need to make a decision concerning the intentions of an adversary. Given response processes of self preservation and a mission of intercepting an enemy, the agent could use probabilistic reasoning techniques to make a decision on whether to proceed or withdraw.

We address this problem by using probabilistic ontologies (Costa et al., 2007; Costa et al. 2009) as the technique for representing uncertainty and performing inferential reasoning in support to battlefield decisions. The mathematical framework supporting the technique is multi-entity Bayesian networks (MEBN), which provides adequate formal support for representing a joint probability distribution over situations involving unbounded numbers of entities interacting in complex ways (Laskey, 2008). This is a major requirement to achieve principled representation of the multiple, multi-modal sensor input and their compounded interactions, such as those a Cognitive Agent will face in a combat situation (Costa, Herencia-Zapana, Laskey, 2012).

In our current research stage, we are developing the interface between the probabilistic graphical reasoner used to develop the decision behaviors for the Cognitive Agent – UnBBayes-MEBN (Matsumoto et al., 2011) and the simulation environment, which is described in the next Section.

4) Investigating the Framework

We plan on pursuing a three phase experimental assessment of the HyCCo framework.

The main COTS tool used will be MÄK VR-Forces (MAK, 2016), a powerful and flexible simulation environment for scenario generation. It has all the necessary features for developing Computer Generated Forces (CGF) to simulate a complex operational environment. Figure 4 depicts an operational scenario we intend to use in future experiments.

The three planned phases are:

1) Assessment of the Autonomy Framework using Agent Based Modeling with simulated Robotic Entities;
2) Implementation and assessment of Virtual Hybrid Teams in an Entity Level Simulation;
3) Implementation and assessment of Hybrid Teams of Humans and virtual robotic entities in an Entity Level Simulation;

Figure 4 – MÄK VR Forces Simulation Environment

In Phase 1, we will implement a simple scenario with only one type of vehicle, and two response processes: self-preservation and accomplish mission goal, as described in Section 3. We will use a large number of vehicles and implement a Monte Carlo approach. The scenario is based on a "capture the flag" situation, in which the target is protected by enemy vehicles, while the blue vehicles will attempt to get to the target using different organizational structures. In the experiments, our goal is to investigate what type of organizations and DDRs are most effective. We will also assess the correctness and performance of the basic construction of the framework.

In Phase 2, we will use the mission simulation capability of VR-Forces to construct a number of detailed scenarios that involve humans and robots interacting to accomplish a mission. We will develop these scenarios completely within the simulation tool and perform additional sensitivity testing on the HyCCo framework, assessing the autonomy levels and the DDR.

In Phase 3, we will introduce human-in-the-loop interfaces to allow for humans to collaborate with simulated entities. In this phase, we intent to have humans acting in the simulation as highly autonomous machines, which will allow us to assess and measure factors such as planning and trust in hybrid teams.

5) Conclusions

In this paper we have developed a concept of autonomy for hybrid teams. This is a key aspect for future operations, which will include an IOIT environment where advanced capabilities will be available to machines and robotic entities. We are designing the HyCCo framework as a means to support future technical specifications (e.g. interfaces for devices in the IOIT) to "build in" the ability to specify autonomy.

There are several issues that were not discussed with respect to our HyCCo Framework. These include how to communicate intent – the overall goal of a mission (Gustavsson et al., 2011; Schade & Hieb, 2007), an aspect that is typically understood by trained military personnel but its use with HyCCo is still not well studied.

Similarly, trust is a major issue that needs to be addressed (Hackman, 1998). Even in human teams, there are many factors that can cause failure (Hieb, 2015). In a true hybrid team, there needs to be an understanding that the collaboration will yield results and that expectations will be met.

Finally, the HyCCo framework needs to have various planning models developed so to facilitate collaboration in a mission setting. The current mission planning models might not necessarily work as originally intended, and may need to be augmented or changed to accommodate hybrid teams. HyCCo is an initial attempt to address this issue.

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