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Command and Control Decision Aids for Robotic Autonomous Systems at the Edge

Jonathan Smith[1], Derek Warter[1], Manuel Aguas[1]

[1]DEVCOM Armaments Center, Picatinny Arsenal, NJ

ABSTRACT

Autonomous and robotic platforms have the capability to dramatically increase the forward soldier's ability to gather data and project lethal force across the battlefield. To efficiently leverage these enablers, soldiers will need to understand their platforms and how they can be utilized at critical moments on the battlefield. They will need decision aids that expedite their ability to assess the capabilities and courses of action available to them. Those decision aids need to be informed by resilient data models and networks that are capable of keeping pace with the rapidly changing technologies the soldier is being supplied with.

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1. INTRODUCTION

As warfare becomes increasingly information-centric at all echelons up to the edge, an unprecedented volume of data has become available to warfighters. If properly analyzed and exploited, rich data may augment combat effectiveness to a decisive degree. However, increasing data density, even when filtering for irrelevant information, will invariably induce cognitive burdens upon human warfighters may result in an overall decrease in combat effectiveness. Introducing nascent technologies such as robots and autonomous systems into the collective set of available sensors and actors exacerbates the issue, further increasing the burden on users. As we continue to increase the soldier's ability to project force on the battlefield, we increase the scope of information the individual must process to accomplish the mission. Consequently, individuals are often required to make critical decisions under significant pressure with an increasingly complex and intricate view of the battlefield. This effort is aimed at enabling autonomous, lethality-based decision aiding algorithms for Robotic Autonomous Systems (RAS) and Counter Unmanned Aerial System (UAS) / Precision Targeting systems capable of running on low power hardware at the edge. The context of the effort is to examine a soldier commanding a heterogeneous group of autonomous systems and how a Command and Control (C2) system enabled with platform specific decision aids assists the user in accomplishing their mission. We will examine three major areas of effort:

1. Providing analytics that accurately measure specific robotic or autonomous system capabilities.
2. Provide battlefield analysis that refines the potential courses of action a soldier can take into those most relevant for consideration.
3. Leverage a communication protocol that can encapsulate all relevant information a warfighter needs to consume or communicate.

These considerations were examined as part of DEVCOM Armaments Center's Collaborative Networked Armaments Lethality Technology (CNALT) project.

2. PLATFORM-SPECIFIC PERFORMANCE QUANTIFICATION

To quantify the performance of heterogeneous robotic platforms, we define a set of key performance metrics. The metrics may include mobility, which evaluates the platform's ability to navigate and reach desired locations based on factors such as speed, range, and terrain traversability. Perception assesses the platform's sensing capabilities, including field of view, resolution, and ability to detect and track objects of interest. Payload capacity quantifies the platform's ability to carry and manipulate payloads, such as tools or equipment required for task execution. Endurance measures the platform's operational duration based on factors like battery life or fuel capacity. To enable meaningful comparisons across diverse platforms, these performance metrics are normalized using min-max normalization to scale the values to a range of 0 to 1. This normalization technique ensures that all metrics are represented on a common scale, with 0 indicating the minimum performance and 1 indicating the maximum performance. By representing all performance metrics on a 0 to 1 scale, we create a unified framework for evaluating and comparing heterogeneous robotic platforms.

Currently, our approach focuses on allocating a single autonomous robot to execute one task at a time. We evaluate all available robots against each task using the normalized performance metrics and generate a table scoring each robot-task pair accordingly. However, this brute-force method becomes computationally expensive as the number of robots and tasks increases. To address this challenge, we are exploring linear optimization and greedy solutions to efficiently allocate robots to tasks without exhaustively evaluating all possible combinations. These optimization techniques aim to find the best robot-task assignments while considering the normalized performance metrics and any additional constraints or objectives. Furthermore, we are investigating the problem of allocating multiple autonomous robots to complete a single task. In this scenario, the order in which the robots execute their sub-tasks can significantly impact the overall performance of the mission. For example, determining whether robot 1 should perform its sub-task before robot 2, or vice versa, is not always evident to an autonomous system, even if it may be intuitive to a human operator. When combining the problems of finding the best robot for a task and allocating multiple robots to a single task, we encounter a combinatorial explosion of possible solutions. For instance, given three robots (A, B, and C) and a task T, there are multiple ways to allocate the robots:

- A can complete task T
- B can complete task T
- C can complete task T

- A and B can complete task T
- A and C can complete task T
- B and C can complete task T
- A, B, and C can complete task T

To tackle this combinatorial problem, we need to develop efficient algorithms that can explore the solution space intelligently, considering the performance metrics of individual robots and the potential synergies or conflicts when combining multiple robots for a task.

While our proposed platform-by-platform approach lays the foundation for quantifying and optimizing the performance of heterogeneous robotic systems, there are several avenues for future research:

1. Developing advanced optimization algorithms that can efficiently handle the combinatorial nature of multi-robot task allocation while considering the normalized performance metrics and additional constraints.
2. Investigating the impact of different robot-task allocation strategies on the overall system performance, including the trade-offs between optimality and computational efficiency.
3. Exploring the integration of machine learning techniques to adaptively learn and refine the performance metrics based on real-world data and feedback, enabling the system to improve its task allocation decisions over time.
4. Conducting extensive simulations and real-world experiments to validate the effectiveness of the proposed approach in various scenarios and identify potential limitations or areas for improvement.
5. Extending the framework to consider dynamic and uncertain environments, where the performance metrics and task requirements may change over time, requiring adaptive and resilient task allocation strategies.

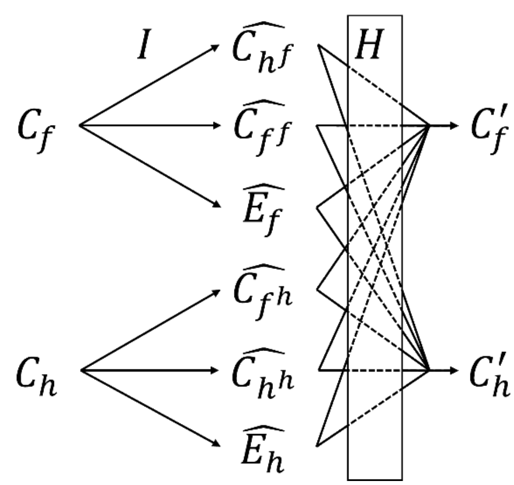
By addressing these research challenges, we aim to develop a comprehensive and scalable framework for optimizing the performance of heterogeneous robotic systems in complex, real-world applications.

3. AGGREGATING HEURISTICS

Consider that episodes of combat may be modelled as a series of discrete transformations upon combatant states.

$$C^{'} = \sum_{i=0} T(C) \quad (1)$$

Under this model, episodes of combat are broken into combatant states C before an engagement, the sum of transformation functions T, each of which reveal the effects of one or more engagements at interval i, and the subsequent combatant states C' after the series of engagements. Combatant states comprise all pertinent information about the condition of each combatant, such as location, logistical information, and health. Engagements are represented by transformation functions that may be generalized thusly:



(2)

Friendly combatants C_f and hostile combatants C_h use their respective decision-making processes I to specify intended actions and outcome states with respect to themselves $\widehat{C_{x^x}}$, each other $\widehat{C_{y^x}}$, and the environment $\hat{E}$. Combatants take steps to manifest their respective desired outcomes via engagement H. H is an opaque (hidden) process beholden to not only the intentions of combatants, but also external factors. The mission of any combatant commander is to generate an intention stack that will influence the engagement process such that favorable outcome states are achieved. That is, commanders must optimally select the allocation of their forces to the set of possible actions upon the enemy or the environment. There are three necessary steps to generate an optimal intention stack in the discrete model of combat.

1. Possible actions must be enumerated.
2. The predicted effects of individual actions must be evaluated. The predicted effects must be relevant and accurate.
3. A set of individual actions must be chosen such that the combined predicted effect of all selected actions is maximally favorable to the commander.

This process may be notated as follows:

$$\begin{aligned} A &= \left\{\{a_{c1}, \dots, a_{cn}\}\forall c; c \in C\right\} \qquad (3) \\ A' &= \{f(a)\forall a; a \in A\} \\ I' &= \left\{\{a_{ci} | a'_{ci} = \max(A'_c)\}\forall c; c \in C\right\} \end{aligned}$$

The number of operations required to calculate the optimal intention stack I' varies according to the size of the possible action set A. For the case where all actions are optional for each friendly combatant c, and many-to-one allocations of friendly combatants to action receivers (enemies or other objects) are allowed, the number of required operations is proportional to

$$O_{c_f c_h} = \sum_{i=0}^{c_f c_h} \binom{(c_f c_h)-1}{i} O_i \, [1] \qquad (4)$$

While the optimal intention stack according to a given heuristic set may be calculated in polynomial time, the number of required operations grows in a combinatorial manner not conducive to efficient resolution.

Because a brute-force solution cannot be efficiently calculated, other approaches to locating an optimal intention stack must be considered. If actionable targets are prioritizable, then a naïve greedy search may be employed. In a greedy search, a new set of heuristics are employed to generate a ranking of actionable targets according to the perceived desirability of actioning them. This method approximates the opportunity cost of actioning any given target. Once targets are prioritized, the optimal actor or actor subset for each target may be selected. Paired targets and actors are stricken from further consideration, and the algorithm continues in this manner until no targets or actors remain. This reduces the required number of operations from a sum of combinatorials to

$$O_{c_f c_h} = \sum_{i=0}^{c_h} c_f - i \qquad (5)$$

in the worst case, where $c_f > c_h$. This method of resolution is computationally inexpensive. However, it assumes no interdependencies in those characteristics of each target state that are relevant to prioritization heuristics. If

$$P\left(c_{h_1}, c_{h_2}\right) > P\left(c_{h_1}\right) + P\left(c_{h_2}\right) \qquad (6)$$

where P is a target saliency scoring function, then a greedy search may not find a globally optimal intention stack.

Parametric methods of intention stack generation must sacrifice completeness for efficiency, and if effect prediction heuristics are inaccurate, the output may be incorrect regardless. An empirical approach to effect prediction and intention generation may bridge the shortcomings of parametric approaches. By combining a combat simulation with a regressed utility prediction model and a reinforced policy model, it may be possible to approach globally optimal intention stacks without sacrificing computational efficiency. Under this methodology, hand-made heuristics are replaced with regressive models that train on historical data or a combat simulator to predict the expected utility of each engagement. Thus, reliance upon accurate heuristics is replaced with the requirement for adequate historical data or an accurate simulator. Once scoring heuristics are generated, a policy model may be optimized against the heuristic model to enable intention stack generation.

4. RESILIENT COMMUNICATION PROTOCOL

The increased capabilities available to our soldiers as we move to a robotic equipped army must be enabled by interfaces and data protocols capable of transmitting the correct information to the correct point on the battlefield. This requires the identification of what data is critical for consumption both by the soldier and by the robotic platforms in addition to how that information will be provided. This process is defined as productizing data. This effort explored leveraging an extensible-hierarchical data protocol that would allow for the rapid expansion of what data is encapsulated by the protocol as well as allowing different levels of information resolution to be defined.

In traditional protocols there are often a small list of legal values that can be used to define what data is able to be encapsulated by the protocol. If a capability or entity is not coded into the standard it cannot be represented or represented correctly on the network due to the limitations of the protocol. Extending or updating the protocols to encapsulate more information can be costly and time consuming as it requires coordination with the current users of the protocol and potential rework of the software leverages it. As a consequence, the rapid deployment or implementation of new platforms and capabilities can be hampered by the ability of the network to be able to encapsulate the information that is required for them.

This effort leveraged an extensible hierarchical data protocol to enable robotic platforms to report their capabilities to the level of fidelity that they are able. Network entities consume the hierarchical protocol from the greatest level of abstraction down to the most specific information they are capable of leveraging. Any information the network entity is not capable of consuming is ignored. To illustrate this concept take the example relocate message being sent to a robotic platform. In a traditionally defined protocol the message definition would be similar to the following:

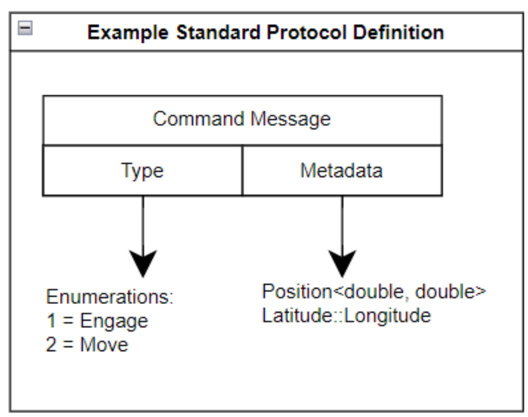


Figure 1: Example Standard Message Construction

As shown in Figure 1, the message can either transmit a command to Engage or to

Move. Both command messages include location as the associated metadata. Now let us assume a new variant of the autonomous system has been introduced and it has the capability of relocating along a user defined path or it can determine its own course and navigate autonomously to a final position. A new message or message variant would need to be defined to handle the transmission of the route. The additional message type of "Route" has conflicting metadata to the original message. As shown in Figure 2.

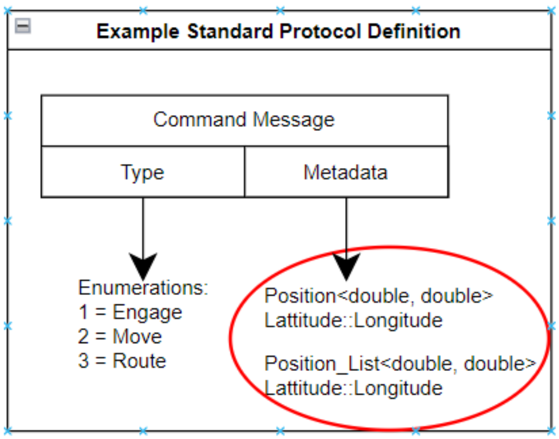


Figure 2: Extended Standard Message with conflicting meta data definitions.

Now lets assume that there is a heterogeneous mix of platforms on the battlefield where some (group A) have the ability to navigate via a user provided route or autonomous navigation and some (group B) only have the ability to navigate via autonomous navigation. Either the user or the tasking system will need to know the capabilities of the platform it is attempting to task in order to task them correctly.

However, with the hierarchical defined data protocol the original relocate message can be extended as shown in Figure 3.

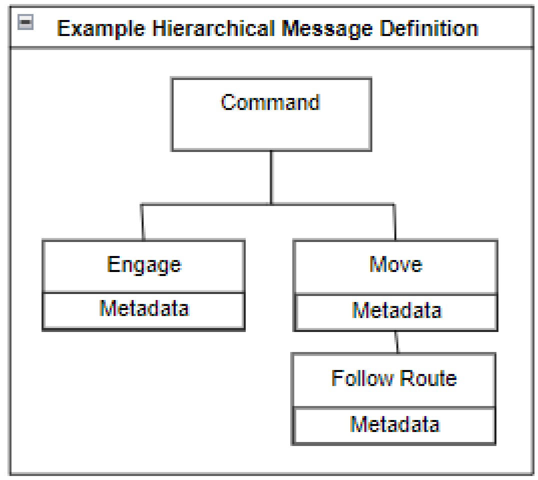


Figure 3: Hierarchical Message allowing extension of base level command messages.

Systems parse the message from its top level or broadest rank to its most specific. In this instance the C2 system sends out one command to all of the receiving systems and they parse the message to the level they are capable of understanding. The receiving systems can acknowledge the resolution at which they can decipher the message by reflecting that resolution in a message acknowledgement as demonstrated in Figure 4.

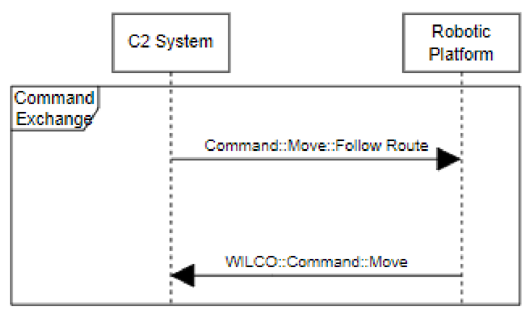


Figure 4: Receiving system acknowledges receipt of a message and indicating its level of compliance to the communicating system

While the hierarchical protocol allows for a more extensible and resilient communication, it is reliant on the broad categories of information and actions that a user would want to communicate to have been identified and provided in the standard. For this reason it is paramount that higher abstractions within the protocol accurately reflect the functions and information that users are interested in leveraging. If those are done correctly, the detail and resolution of that information can be easily modified and communicated to match the system needs.

4.1. Drawbacks of Hierarchical Data Protocol

The protocol was not without drawbacks, the verbose definition of the messages requires significantly more bandwidth then compared traditional messages. The ability to easily extend the messages can also lead to collisions between different entities extending the same core message definitions. The application of data compression algorithms may assist in mitigating the increased bandwidth, and unique identifiers attached to the protocols version may also allow conflicting protocol extensions to be deconflicted.

5. CONCLUSION

We found that creating normalized platform specific performance analytics was enabled by leveraging an extensible and flexible communication protocol that allowed for platform specific data reporting as well as enabling the user to issue platform specific commands. While there is still more work to be done to find efficient means of prioritizing and simplifying the analysis, the system is successful in providing simplifications of critical data factors to inform decisions when leveraged on small data sets.

6. REFERENCES

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