The AAAI 2017 Spring Symposium on
Computational Context: Why It's Important, What It Means, and Can It Be Computed?
Technical Report SS-17-03

Framework for Multi-Human Multi-Robot Interaction: Impact of Operational Context and Team Configuration on Interaction Task Demands

R. Dirk Beer, Ph.D.
Pacific Science & Engineering Group
San Diego, CA 92121
dirkbeer@pacific-science.com

Cory A. Rieth, Ph.D.
Pacific Science & Engineering Group
San Diego, CA 92121
coryrieth@pacific-science.com

Randy Tran, M.A.
Pacific Science & Engineering Group
San Diego, CA 92121
randytran@pacific-science.com

Maia B. Cook, Ph.D.
Pacific Science & Engineering Group
San Diego, CA 92121
maiacook@pacific-science.com

Abstract

Increasing prevalence and complexity of robotic and autonomous systems (RAS) and promising applications of hybrid multi-human multi-RAS teams across a wide range of domains pose a challenge to user interface designers, autonomy researchers, system developers, program managers, and manning/personnel analysts. These stakeholders need a principled, generalizable approach to analyze these teams in an operational context to design effective team configurations and human-system interfaces. To meet this need, we have developed a theoretical framework and software simulation that supports analysis to understand and predict the type and number of human-RAS and human-human interaction task demands imposed by the mission and operational context. We extend previous research to include multi-human multi-RAS teams, and emphasize generalizability across a wide range of current and future RAS technologies and military and commercial applications. To ensure that our framework is grounded in mission and operational realities, we validated the framework structure with domain experts. The framework characterizes *Operational Context*, *Team Configuration*, and *Interaction Task Demands*, and defines relationships between these constructs. These relationships are complex, and prediction of Interaction Task Demands quickly becomes difficult even for small teams. Therefore, to support analysis, we developed a software simulation (Beer, Rieth, Tran, & Cook, 2016) that predicts these demands and allows testing and validation of the framework. The framework and simulation presented here provide a step forward in the development of a systematic, well-defined, principled process to analyze the design tradeoffs and requirements for a wide range of future hybrid multi-human multi-RAS teams.

Introduction

Robotic and autonomous systems (RAS) are increasing in prevalence, growth, and complexity. The importance of these systems is highlighted in recent DOD strategy documents, which describe many applications for agile, multi-human multi-RAS teams (e.g., U.S. Army, 2015; U.S. Air Force, 2015; U.S. Department of Defense, 2013). This growth is also apparent in commercial (e.g., warehouse and delivery logistics) and industrial applications (e.g., automated mining). In addition, the hybrid human-RAS teams and their operational contexts are becoming increasingly complex (e.g., heterogeneous teams, large numbers of vehicles, novel autonomous capabilities such as swarming, simultaneous support of multiple commands and missions, changing mission demands). This increasing prevalence and complexity is a challenge for user interface designers, autonomy researchers, system developers, program managers, and manning/personnel analysts, who need help understanding and predicting the operational feasibility, tradeoffs, and impacts of human-RAS team configurations within operational contexts. These stakeholders need a principled and generalizable approach to analysis of their problem.

To meet this need, we have developed a theoretical framework and software simulation that supports principled analysis of these systems to understand and predict the type and number of human-RAS and human-human interactions required. This information can then be used to inform system design and team configuration. The framework leverages the wealth of relevant existing research on human interaction with multi-RAS systems (e.g., Cummings & Guerlain, 2007; Nam, Johnson, Li, & Seong, 2009; Olsen & Wood, 2004; Whetten, Goodrich, & Guo, 2010; Yanco & Drury, 2004). We built on this previous research by expanding our framework to include multi-human multi-RAS teams. In addition, we emphasized generalizability of the framework across a wide range of current and future RAS technologies, and across a wide range of military and civilian applications. To achieve this generalizability, we structured the framework around commonalities in the factors describing operational context across technologies and applications. To ensure that our framework was grounded in mission and operational realities, we validated the framework structure with military and civilian domain experts. To help further clarify and validate the framework and to work toward actionable tools for analysis and design, we created a software simulation that implements framework constructs, and counts the number of human-RAS and human-human interactions demanded by a specified operational context and team configuration. This simulation supports analysis of tradeoffs between different team configurations and of the effects of changing operational context.

The multi-human multi-RAS (henceforth, multi-human/RAS) interaction framework consists of two inputs: Operational Context and Team Configuration, and one output: Interaction Task Demands. The first input, "Operational Context", characterizes the broad operational factors that impact human-RAS interaction task demands. These factors inform the interaction tasks needed in the team. For example, a team operating across multiple areas, serving multiple commands, will have more interaction tasks related to awareness of varying environmental conditions and coordination of multiple missions than a team serving a single area and command. The second input, "Team Configuration," specifies the scheme for distributing the human-RAS and human-human interaction tasks among humans. There are many possible ways to do this, for example assigning each human to a RAS, or assigning humans to specific functions across many RAS. As new technology capabilities such as swarming systems or highly autonomous systems are developed, novel unconventional configurations become possible and should be explored with the aim of taking full advantage of these new capabilities. Lastly, the output of the framework, "Interaction Task Demands", characterizes and accounts for the type and number of demands per human resulting from the combination of Operational Context and Team Configuration. These Interaction Task Demands can be thought of as the predicted task and cognitive load on humans due to interaction tasks imposed by the Operational Context and assigned by the Team Configuration. Through the metric of Interaction Task Demands, the framework supports analysis of the impacts of changing Operational Context (e.g., an increasing number of RAS available for the mission). It also supports analysis of trade-offs between different Team Configurations.

The goal of our framework is to clearly characterize the multi-human/RAS team design problem, and to support analysis and understanding of the problem. Once the problem has been adequately characterized using our framework, multiple potential solutions, and methods for implementing these solutions, become possible. For example, a demand for energy and health status monitoring of multiple RAS could be supported through user interface design, improved automation, training, or increased manning. These all are ways of managing the actual, realized cognitive and task load on the humans to achieve best team performance. The Interaction Task Demands identified by the framework can be used as inputs in the process of developing a solution (e.g., user interface design through user-centered design (Norman, 1988, 2009, 2013) or ecological interface design (Burns & Hajdukiewicz, 2004)).

The following sections describe the three parts of our framework.

Operational Context

Given the vast range of potential applications, task environments, users, and scale of multi-human/RAS systems, the consideration of operational context is vital. To design and field hybrid systems for such a vast range of use, a logical first step is to identify the most important and impactful factors of the context in which the human-RAS team will operate. We approached this by (1) surveying and analyzing a wide range of possible future military and civilian applications of multi-human/RAS systems, (2) analyzing existing human-robot interaction taxonomies, and (3) regularly reviewing our results with military, robotics, and autonomy subject matter experts.

From this analysis, we propose that three broad categories of Operational Context, shown in Figure 1, capture the factors most relevant to human-RAS interactions. These are (1) the *Mission Focus,* which represents *what* the team is trying to accomplish, i.e., the main goals of the team and the types of tasks needed to achieve those goals; (2) the *Application Constraints*, which are the *limits* on how the team can work towards its goals in the specific application domain, and (3) the *Team Capabilities*, which describes *how* the team can accomplish its goals, i.e., the specific capabilities and resources of the team's humans and RAS. For each category of Operational Context, there is a wide range of possibilities, which makes a manageable, systematic characterization difficult. To address this difficulty, we identified commonalities that allow a simplified characterization of the wide range of systems and domains surveyed. The goal of this characterization was akin to that of principal components and cluster analyses – to reduce the many-dimensional space of Operational Context to a manageable number of minimally overlapping factors and factor levels. These then provide the essential information needed to understand the implications for multi-human/RAS interaction. The following subsections describe each category of Operational Context we derived.

Operational Context: Mission Focus

Multi-human/RAS teams address a wide array of current and future military and civilian needs, and every mission can be decomposed into one or more goals that the team is working to achieve. Previous taxonomies and frameworks have represented categories of task context (e.g., Dudek et al., 2002). These have included application domains themselves (e.g., Agah, 2000; Thrun, 2004), specific functions supported by robots such as urban search and rescue (Yanco & Drury, 2002, 2004), and tasks being performed by robots (J. Beer et al., 2014).

In our analysis, we draw on the fact that mission-related goals are typically associated with a characteristic set of tasks. Rather than attempt to create an exhaustive taxonomy of the goals and tasks in all domains, we performed an analysis to identify clusters of these goals and tasks that are independent of the specific applications (e.g., military or civilian, aerial or ground-based) and technologies (e.g., highly autonomous or requiring more human intervention). The following six goal and task clusters of "Mission Focus" factors emerged, describing *what* the team is trying to accomplish: *Transit*, *Area*, *Target*, *Resource*, *Construction*, and *Assistive* (Figure 1, top). Missions or operations may include just one of these Mission Focus factors (e.g., *Transit* of a delivery drone to and from the recipient's location), but more typically they consist of a combination of Mission Focus factors (e.g., a man-overboard search would involve *Transit* to the last known location, and search for the *Target*). We define these Mission Focus factors in terms of goals:

Transit: Goal is directed movement from one location to another, e.g., movements of RAS, goods, or assets from one location to another.

Area: Goal is relevant to some area, such as mapping, coverage, or exploration of an area. While some movement is needed to support this goal, the hybrid team tasks and human-RAS interactions are primarily focused on things related to the area, rather than movement.

Target: Goals and activities are related to a target, such as search for a target or defense of a specific target.

Resource: Goals and activities relate to monitoring and managing resources at a location or between locations; e.g., resupply or warehouse logistics.

Construction: Goals and activities involve building or constructing structures.

Assistive: Goals are social interaction or assistance, and activities primarily relate to those social, cognitive, or physical interactions.

This breakdown provides a useful clustering of similar goals because each cluster is associated with a characteristic set of tasks. For example, *Transit* requires tasks related to navigation, while *Target* requires tasks related to identification and tracking. Tasks associated with each goal- and task-cluster usually occur in close proximity in time, and are likely to share similar information needs and task products.

Operational Context: Application Constraints

Hybrid teams involved in military or civilian/commercial operations operate within various technology, environmental, and mission-related constraints. The importance of these types of constraints has been highlighted in other frameworks and research (e.g., Scholtz & Bahrami, 2003; Yanco & Drury, 2002, 2004), which have included categories such as mission duration and resource limits (Balch, 2002), and environmental attributes (Huang et al., 2005; Scholtz & Bahrami, 2003).

The wide variety of possible applications makes it more difficult to derive an exhaustive set of clusters of these constraints as was done for Mission Focus. However, based on the previous research and our analysis, we propose a set of categories of "Application Constraints." While Mission Focus describes *what* needs to be accomplished (i.e., goals and types of tasks), Application Constraints *limit how* those can be accomplished. The categories include *Environmental, Communications*, and *Mission*-related constraints (Figure 1, middle). They are given here with examples:

Environmental/survivability: Need for robustness, expected level of attrition, failure rates.

Communications: E.g. bandwidth, latency, available type, frequency, duration, likelihood and severity of denied communications/jamming.

Mission: Need for stealth, speed, persistence; accountability.

Application Constraints limit how the team can accomplish its Mission Focus goals and tasks. For example, navigation tasks during *Transit* of an aerial RAS can often take advantage of real-time communication, while navigation tasks during *Transit* of an underwater RAS are likely to involve intermittent or very low bandwidth communication. These constraints also inform what RAS capabilities are required. For example, in a denied communications environment, robots capable of highly adaptive, autonomous behavior may be required.

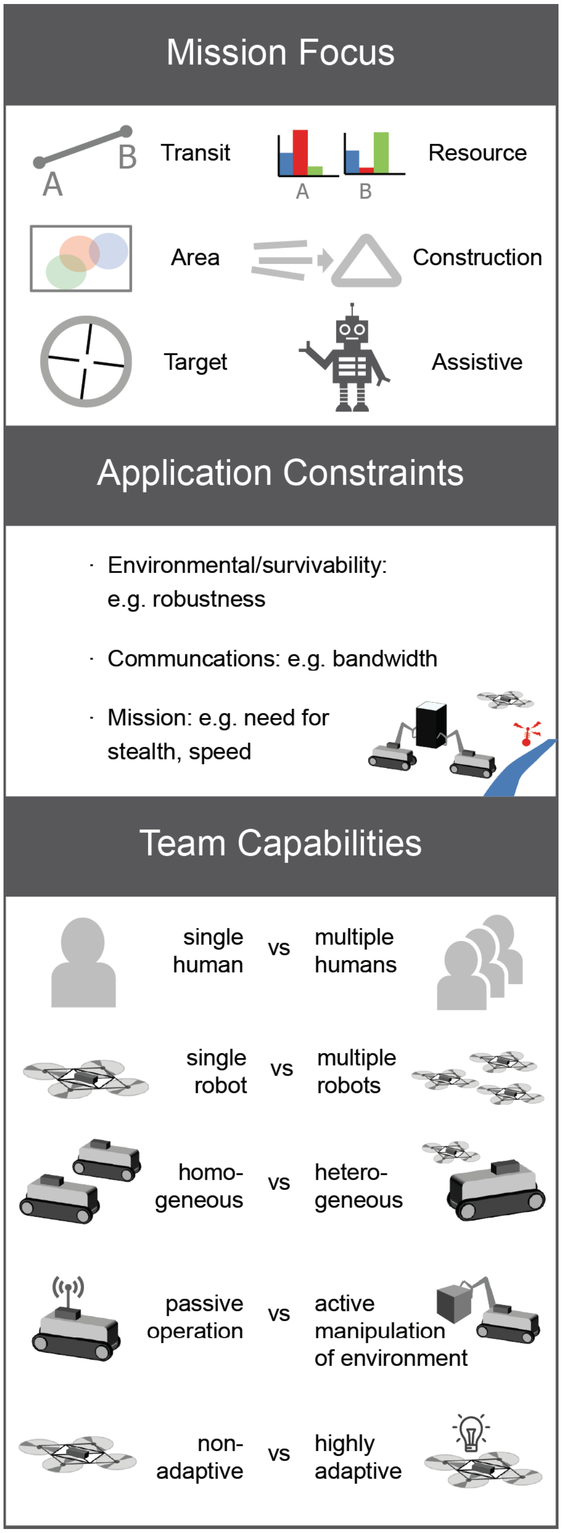

Figure 1 - The Operational Context constrains and defines how roles will be allocated and the tasks that will be performed.

Operational Context: Team Capabilities

Team capabilities determine *how* the team can accomplish *Mission Focus* goals and tasks within the limits of the *Application Constraints*. What capabilities does the team have to accomplish its goals within the constraints? Previous research has also considered RAS capabilities, such as robot level of automation (e.g., Agah, 2000; J. Beer et al., 2014; Dudek et al., 1996, 2002; Goodrich & Schultz, 2007; Granda, Kirkpatrick, Julien, & Peterson, 1990; Thrun, 2004; Yanco & Drury, 2002, 2004) and physical properties of robots/robotic agents (e.g., Scholtz & Bahrami, 2003; Yanco & Drury, 2004).

Through our analysis of a wide range of possible future multi-human/RAS team applications, we identified major categories of "Team Capabilities" that impact how the hybrid team can accomplish its goals (Figure 1, bottom). The categories include the number of humans (*Multiple* vs. *Single Humans*), the number of RAS (*Multiple* vs. *Single RAS*), the composition of the RAS team members (*Heterogeneous,* having varied capabilities allowing complementary execution of tasks, vs. *Homogenous,* having identical capabilities), the type of interaction of the RAS with the environment (*Active Manipulation,* requiring human approval*,* vs. *Passive Operation* such as sense, collect, and interpret), and the level of automation of the RAS (*Highly Adaptive/Autonomous* vs. *Less Autonomous*). These capabilities impact *how* the team can address different *Application Constraints* (e.g., RAS that are *Highly Adaptive/Autonomous* and can operate without human intervention may be well-suited for a communications-limited environment) and *how* the team can accomplish its Mission Focus goals (e.g., hybrid human-RAS teams doing Construction are doing *Active Manipulation* of the environment and require human override capabilities). These Team Capabilities categories can be tailored or expanded as technologies evolve.

Team Configuration: Assigning Interaction Tasks within an Operational Context

Previous research has addressed the distribution of tasks between humans and RAS in detail ("task allocation", e.g., Crandall & Goodrich, 2002; Martin et al., 2016; Parasuraman & Riley, 1997; Parasuraman, Sheridan, & Wickens, 2000; Scerbo, Freeman, & Mikulka, 2003). We do not reconsider human vs. robot task allocation here; in most cases, that allocation is built into the RAS technology, and thus can be specified as part of the Team Capabilities. Instead, we consider *Interaction Tasks* within the Operational Context, and consider the possible *Team Configurations* for distributing those *Interaction Tasks* among the humans in the system.

We define *Interaction Tasks* as those tasks at the interface of humans and RAS, and between humans and other humans related to RAS operation, since these are the tasks most relevant to human-RAS interaction and *Team Configuration* (Figures 2 & 3). Enumerating and understanding the impact of all required *Interaction Tasks* is critical to a system design that takes humans into account, and is often neglected. Examples of *Interaction Tasks* are a human setting geographic boundaries for a highly autonomous RAS that is imaging cropland, or a human monitoring remaining range of a swarm of undersea RAS conducting a mine search. Tasks carried out exclusively by the human are important to consider when estimating the overall demands on the human operator. While outside the scope of the analysis reported here, the demands on the human operator from tasks conducted exclusively by the human could be factored in to develop an overall characterization of human operator task demands. Tasks conducted exclusively by the RAS that do not affect the human operator (e.g., autonomous image acquisition) are not considered here.

There are many possible *Team Configurations*, and each has different implications for user interfaces and team robustness. For example, as shown in Figure 2 (top), each human could be assigned all *Interaction Tasks* (e.g., navigation control, health monitoring, monitoring status of sensor collection, etc.) related to a RAS. With this Team Configuration, each human is responsible for multiple task types, but only one instance of each type. This has implications for user interface design, and for the robustness of the Team Configuration as the Operational Context changes. For example, if the *Team Capabilities* are improved by increasing the number of RAS (compare Figure 2, top, to Figure 2, bottom), each human must contend with an increasing number of RAS and their associated Interaction Tasks. Alternatively, a human could be assigned only one type of *Interaction Task* for all RAS on the team (Figure 3). This configuration might lead to more efficient team and task management even as the number of RAS increases, and it might also benefit from more specialized user interfaces. To take full advantage of emerging capabilities of hybrid multi-human/RAS teams, alternative Team Configurations should be explored through careful analysis of the benefits and tradeoffs. The next sections describe a metric and an approach for these analyses.

Interaction Task Demands: A measure of the impact of Operational Context and Team Configuration on interaction requirements

Different *Operational Contexts* and *Team Configurations* result in different numbers and types of *Interaction Tasks* and demands on the human operators in the multi-human/RAS team (e.g., monitoring demands). In our framework, we characterize the predicted task and cognitive load on the human operator associated with these Interaction Tasks as "Interaction Task Demands". Prior research has approached the issue of human performance in human-robot teams in terms of operator capacity (e.g., Cummings & Guerlain, 2007; Cummings, Bruni, Mercier, & Mitchell, 2007; Kolling et al., 2016; Mekdeci & Cummings, 2009; Olsen & Wood, 2004; Whetten et al., 2010; Yanco & Drury, 2004) and computational complexity/operator cognitive effort (e.g., Lewis, Wang, & Scerri, 2006). For future multi-human/RAS teams, however, it is difficult to provide estimates of operator capacity (e.g., fan-out, Olsen & Wood, 2004) due to the vast number of possibilities and the rapid pace of technology maturation. Therefore, rather than attempt to provide an estimate of operator capacity, our approach of characterizing Interaction Task Demands provides a means for relative comparison of different team configurations, and estimates for the mitigating effects of automation, interface, training, and manning solutions. Further, future multi-human/RAS teams may be configured in ways that do not assume that a human is responsible for all Interaction Tasks for a single robot. The metric of Interaction Task Demands allows the flexibility to explore and analyze team configurations where humans may have functional- (e.g., assign by task) rather than platform-based assignments (e.g., assign by robot). Finally, Interaction Task Demands can account for the demands on human operators interacting not only with RAS but also with other humans in the multi-human/RAS team. As multi-human/RAS become operational, metrics such as capacity and utilization (percent busy time) as a proxy for workload (Rouse, 1983) could be assessed to provide a more precise estimate of performance.

Our approach is to define *Interaction Task Demands* as the requirements for *Awareness, Coordination, Handoff,* and *Expertise/training* related to any part of the *Operational Context*. For example, in a particular application there may be demand for *Awareness* of the mission and RAS status, for *Coordination* between humans on human-RAS interactions, for *Handoffs* between humans over time or between geographic areas, and for *Expertise or training* related to human-RAS interactions. As Goodrich and Cummings (2015) recently noted regarding multiple UAV control, "…the limiting factor is not the number of vehicles an operator is controlling, but rather the number of tasks generated from each vehicle…". Expanding this point here, any change in Operational Context or Team Configuration can result in changes in the *Interaction Task Demands* on humans, and these demands in total must be met by limited human cognitive and task capacity, or by other interventions such as greater RAS autonomy.

Simulation of Interaction Task Demands

The interactions between Operational Context and Team Configuration are complex, and the relationship with Interaction Task Demands quickly becomes too complex even with fairly simple examples. Yet system engineers, RAS researchers, and user interface designers require answers to basic questions such as: What Team Configurations are feasible (i.e., have a manageable number of *Interaction Task Demands*)? How robust is a hybrid team to changes in the *Operational Context*? How can improved automation help?

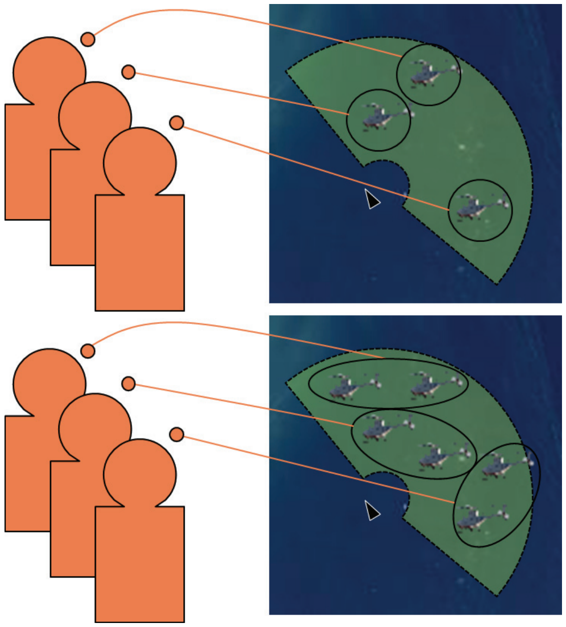

Figure 2 – Assigning humans by robot -- one method of distributing Human-RAS Interaction Tasks among humans: as the number of robots increases, the cognitive and task demand on the humans increases.

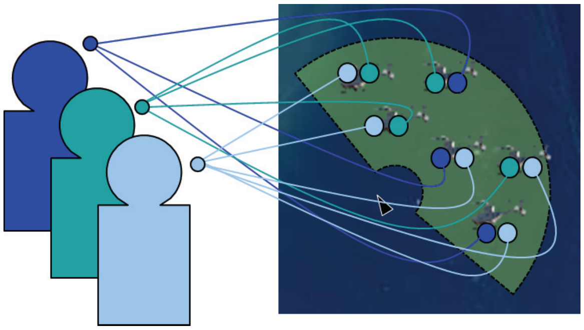

Figure 3 – Assigning human by task type -- an alternative method of distributing Human-RAS interaction tasks among humans. Different methods of distributing tasks among humans can result in potentially beneficial effects on cognitive and task demands, or more robustness to scaling.

To answer these questions, and to help clearly define the constructs in our framework, we have developed a software simulation tool that computes multi-human/RAS team Interaction Task Demands in an Operational Context for several possible Team Configurations as a set of well-defined parameters, and calculates the resulting demands (Beer, Rieth, Tran, & Cook, 2016). The simulation is necessarily a simplified version of the framework (as described below), but the parameters chosen represent important considerations in realistic hybrid multi-human/RAS application missions and operations, and provide a concrete test of our framework.

Briefly, the simulation calculates Interaction Task Demands by first listing all Interaction Tasks produced by the Operational Context. Second, it assigns those tasks to humans based on the specified Team Configuration using a hybrid heuristic/probabilistic assignment algorithm. Third, it does an accounting of how many Interaction Tasks related to each Operational Context factor each human must contend with, as a metric of *Awareness*-related Interaction Task Demands (i.e., how many task instances a human has to pay attention to). Fourth, it then does an accounting of how many humans have Interaction Tasks related to the same Operational Context factor, for each factor instance. This provides a metric of *Coordination*-related Interaction Task Demands (i.e., how many other humans the human operator has to coordinate with on a specific task).

Through these calculations, which are based on an abstracted, reduced representation of the Operational Context and Team Configuration, and a straightforward, minimalist assignment algorithm, the simulation currently allows side-by-side comparison of the predicted Interaction Task Demand between alternative Team Configurations (Figure 4, bottom left). The simulation also allows analysis of the effect of scaling one Operational Context factor, the number of RAS on the team (Figure 4, bottom right).

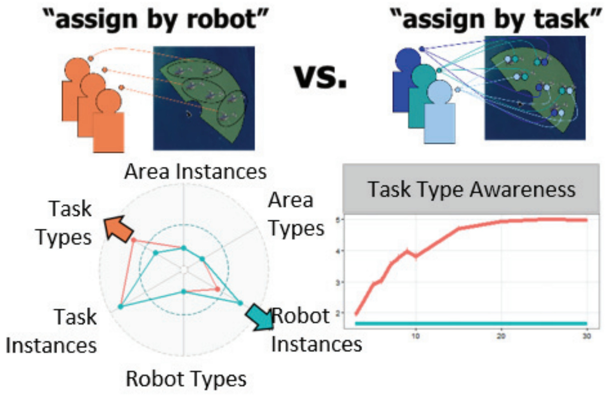

Figure 4 – Simulations comparing the two example alternative Team Configurations. The simulation provides estimates of the resulting cognitive and task demands for the two configurations (example, left graph) and how each type of demand scales as the team is scaled (example, right graph).

Discussion

Operational Context, consisting of Mission Focus, Application Constraints, and Team Capabilities, determines the human-RAS Interaction Tasks required in a team. These Interaction Tasks are assigned to humans through the

Team Configuration, resulting in Interaction Task Demands on each human operator. These Interaction Task Demands must be met by the cognitive and task capacity of the humans in the team. Interaction Task Demands can be mitigated through various means to reduce the burden on humans or to free them for greater impact on mission outcomes.

One way to mitigate demands is through the design of user interfaces and use of appropriate interaction metaphors. The framework helps here because it informs the type and number of tasks that the user interface designs must support. Further, the specific type of demands on the operator can be targeted by specific types of user interface elements and approaches. For example, a demand for Awareness of energy and health status of several RAS can tax the attentional capacity of humans. This high demand can be mitigated through display designs that facilitate attention management. Demand for Coordination on a Geo/mission area can be mitigated through representations such as shared geographic or shared Area coverage task progress visualizations that facilitate coordination.

Interaction Demand can also be mitigated by optimizing the Team Configuration or improving Team Capabilities (e.g., through training, manning and personnel, improved RAS technology, or artificial intelligence). The simulation tool can be used to estimate the effects of these various approaches on Interaction Task Demands.

The framework presented here provides the foundation for a process and tools to analyze the design tradeoffs and requirements for a wide range of future hybrid multi-human multi-RAS teams. Ongoing work includes application, validation, and testing of the framework and simulation on a range of emerging hybrid human-RAS applications, and refinement and expansion of the simulation to provide actionable information to human-RAS stakeholders.

Acknowledgements

This work was sponsored by the Office of Naval Research, contract N00014-14-C-0329. The authors would like to thank Marc Steinberg, the ONR program manager, for advice throughout the project, and Mark St. John of PSE for comments on this manuscript. The views expressed are those of the authors and do not reflect the official policy or position of the Office of Naval Research, Department of Defense, or the US Government.

References

Agah, A. (2000). Human interactions with intelligent systems: research taxonomy. *Computers & Electrical Engineering*, *27*(1), 71–107. https://doi.org/10.1016/S0045-7906(00)00009-4

Balch, T. (2002). *Taxonomies of multirobot task and reward. Robot teams: From diversity to polymorphism*, 23-35.

Beer, J. M., Fisk, A. D., & Rogers, W. A. (2014). Toward a Framework for Levels of Robot Autonomy in Human-Robot Interaction. *Journal of Human-Robot Interaction*, *3*(2), 74–99. https://doi.org/10.5898/JHRI.3.2.Beer

Beer, R. D., Rieth, C. A., Tran, R., & Cook, M. B. (2016). *Team Configuration Simulation for Human Interaction with Multiple Cooperative Robots/Agents*. Pacific Science & Engineering Group, San Diego, CA.

Burns, C. M., & Hajdukiewicz, J. (2004). *Ecological interface design*. CRC Press.

Cummings, M. L., Bruni, S., Mercier, S., & Mitchell, P. J. (2007). *Automation Architecture for Single Operator, Multiple UAV Command and Control*.

Cummings, M. L., & Guerlain, S. (2007). Developing Operator Capacity Estimates for Supervisory Control of Autonomous Vehicles. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *49*(1), 1–15. https://doi.org/10.1518/001872007779598109

Dudek, G., Jenkin, M. R. M., Milios, E., & Wilkes, D. (1996). A taxonomy for multi-agent robotics. *Autonomous Robots*, *3*(4), 375–397. https://doi.org/10.1007/BF00240651

Dudek, G., Jenkin, M., & Milios, E. (2002). *A Taxonomy of Multirobot Systems*.

Goodrich, M. A., & Cummings, M. L. (2015). Human Factors Perspective on Next Generation Unmanned Aerial Systems. In K. P. Valavanis & G. J. Vachtsevanos (Eds.), *Handbook of Unmanned Aerial Vehicles* (pp. 2405–2423). Springer Netherlands. Retrieved from http://link.springer.com/referenceworkentry/10.1007/978-90-481-9707-1_23

Goodrich, M. A., & Schultz, A. C. (2007). Human-robot Interaction: A Survey. *Found. Trends Hum.-Comput. Interact.*, *1*(3), 203–275. https://doi.org/10.1561/1100000005

Granda, T. M., Kirkpatrick, M., Julien, T. D., & Peterson, L. A. (1990). The Evolutionary Role of Humans in the Human-Robot System. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *34*(9), 664–668. https://doi.org/10.1177/154193129003400919

Huang, H. M., Pavek, K., Novak, B., Albus, J., & Messin, E. (2005). A framework for autonomy levels for unmanned systems (ALFUS). *Proceedings of AUVSI Unmanned Systems 2005.*

Kolling, A., Walker, P., Chakraborty, N., Sycara, K., & Lewis, M. (2016). Human Interaction With Robot Swarms: A Survey. *IEEE Transactions on Human-Machine Systems*, *46*(1), 9–26. https://doi.org/10.1109/THMS.2015.2480801

Lewis, M., Wang, J., & Scerri, P. (2006). Teamwork coordination for realistically complex multi robot systems. In *NATO Symposium on Human Factors of Uninhabited Military Vehicles as Force Multipliers* (pp. 1-12).

Martin, L., Bienert, N., Claudatos, L., Gujral, V., Kraut, J., & Mercer, J. (2016). Effects of task allocation on air traffic management human-automation system performance. In *2016 IEEE/AIAA 35th Digital Avionics Systems Conference (DASC)* (pp. 1–8). https://doi.org/10.1109/DASC.2016.7777996

Mekdeci, B., & Cummings, M. L. (2009). Modeling Multiple Human Operators in the Supervisory Control of Heterogeneous Unmanned Vehicles. In *Proceedings of the 9th Workshop on Performance Metrics for Intelligent Systems* (pp. 1–8). New York, NY, USA: ACM. https://doi.org/10.1145/1865909.1865911

Nam, C. S., Johnson, S., Li, Y., & Seong, Y. (2009). Evaluation of human–agent user interfaces in multi-agent systems. *Interna-*

tional Journal of Industrial Ergonomics, *39*(1), 192–201. https://doi.org/10.1016/j.ergon.2008.08.008

Norman, D. A. (1988). *The psychology of everyday things*. Basic books.

Norman, D. (2009). *The design of future things*. Basic books.

Norman, D. A. (2013). *The design of everyday things: Revised and expanded edition*. Basic books.

Olsen, D. R., Jr., & Wood, S. B. (2004). Fan-out: Measuring Human Control of Multiple Robots. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (pp. 231–238). New York, NY, USA: ACM. https://doi.org/10.1145/985692.985722

Parasuraman, R., & Riley, V. (1997). Humans and automation: Use, misuse, disuse, abuse. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *39*(2), 230-253.

Parasuraman, R., Sheridan, T. B., & Wickens, C. D. (2000). A model for types and levels of human interaction with automation. *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans*, *30*(3), 286–297. https://doi.org/10.1109/3468.844354

Rouse, W. B. (1983). *Systems engineering models of human-machine interaction*. New York: North Holland.

Scerbo, M. W., Freeman, F. G., & Mikulka, P. J. (2003). A brain-based system for adaptive automation. *Theoretical Issues in Ergonomics Science*, *4*(1–2), 200–219. https://doi.org/10.1080/1463922021000020891

Scholtz, J., & Bahrami, S. (2003). Human-robot interaction: development of an evaluation methodology for the bystander role of interaction. In *IEEE International Conference on Systems, Man and Cybernetics, 2003* (Vol. 4, pp. 3212–3217 vol.4). https://doi.org/10.1109/ICSMC.2003.1244385

Thrun, S. (2004). Toward a Framework for Human-Robot Interaction. *Human–Computer Interaction*, *19*(1–2), 9–24. https://doi.org/10.1080/07370024.2004.9667338

U.S. Air Force. (2015). *Autonomous Horizons: System Autonomy in the Air Force – A Path to the Future*. AF/ST TR 15-01.

U.S. Army. (2015). *U.S. Army Robotics and Autonomous Systems Strategy Update*.

U.S. Department of Defense (DoD). (2013). *FY2013-2038 Unmanned Systems Integrated Roadmap*. Washington, DC: U.S. Department of Defense.

Whetten, J. M., Goodrich, M. A., & Guo, Y. (2010). Beyond robot fan-out: Towards multi-operator supervisory control. In *2010 IEEE International Conference on Systems Man and Cybernetics (SMC)* (pp. 2008–2015). https://doi.org/10.1109/ICSMC.2010.5641726

Yanco, H. A., & Drury, J. L. (2002). A taxonomy for human-robot interaction. In *Proceedings of the AAAI Fall Symposium on Human-Robot Interaction* (pp. 111-119).

Yanco, H. A., & Drury, J. (2004). Classifying human-robot interaction: an updated taxonomy. In *2004 IEEE International Conference on Systems, Man and Cybernetics (IEEE Cat. No.04CH37583)* (Vol. 3, pp. 2841–2846 vol.3). https://doi.org/10.1109/ICSMC.2004.1400763