Command and Control in Network-Centric Operations: Trust and Robot Autonomy

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Abstract. The rise of the Information Age has not only prompted the mass increase of technological capability, it has promoted the inclusion of new types of team-based network-centric operations. Network-centric operations are founded on the complex and layered connections between interacting physical, information, communication, and social networks. Autonomous intelligent military robots have and will continue to be integrated into these operations. However, the level of interdependency of Soldier-robot team is changing. With advanced technological capabilities for movement, intelligence, and decision making, a military robot will be able to increase its level of independent and interdependent tasking required for effective teaming. For this paper, we will provide a vision of current and future systems, with a focus on capabilities of Soldier-robot teams. This includes discussion of the changing nature of robot autonomy and evolving concepts for communication and control of autonomous intelligent robots. A central and fundamental issue to effective operations is that of trust. We will highlight areas of current systems, near-term developments, and future concepts.

INTRODUCTION

Time and again we see literature pointing to the fact that the conventional battlefield is changing. Moffat (2006) refers to this change in terms of Information Age conflict, which encompasses both conventional (face-to-face) and virtual battlefields. Kott, Buchler, and Schaefer (2014) extend on this description of the Information Age battlefield by identifying the changing dynamics from the conventional to virtual battlefield. One key element is the formation and reliance on networked forms of operations where the number of potential collaborators and the availability of data and information are virtually limitless. According to a report on Network Science by the National Research Council (2005), network-centric or network-enabled operations promote a broadly collaborative and information-rich environment that can be advantageous for military organization and communication across joint, interagency, intergovernmental, and multinational seams and boundaries. Network-centric operations improve information sharing and collaboration that can enhance the quality of information which enables further self-synchronization and improves the sustainability and speed of command, thus increasing mission effectiveness (see Alberts, 2002; Alberts, Garska, & Stein, 1999; Alberts & Hayes, 2003).

Within this paper, we focus on how intelligent, autonomous systems are integrated into these network-centric operations. In particular, the focus of this paper is specific to the way that Soldiers interact with these systems. We anticipate that future systems may be physically embodied, like robots, or non-embodied intelligent software agents that act autonomously. Yet, with both embodied and non-embodied agents, humans will need to interact with the systems in new ways. Within the evolving networked environment, the direction and control of robots and collaborative Soldier-robot performance will be impacted by trust and communications as Soldier-robot interaction evolves from teleoperations to supervisory control to team-like interactions.

Consideration of the Command and Control of Technology

"Command and Control" (C2) has been a specific term that has meant "the exercise of authority and direction by a properly designated commander over assigned and attached forces in the accomplishment of a mission." (Department of the Army FM 3-0. 2008). More recently, the Army has adopted the use of mission command, defined as "the exercise of authority and direction by the commander using mission orders to enable disciplined initiative within the commander's intent…" (Department of the Army, ADP 3-0, 2011, p. 5). The critical aspect of these terms is "command" exercised by a commander, "to achieve the commander's intent and desired end state" (Department of the Army, ADP 3-0, 2011, p.5).

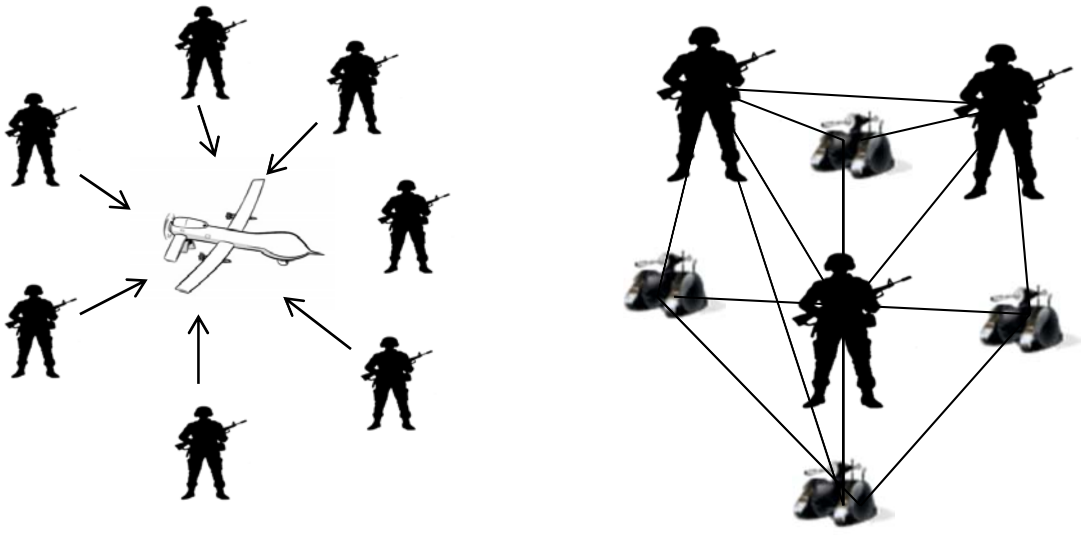
Mission command will be exercised with respect to robotic technology – such technology will be used to accomplish the commander's intent and desired end state. However, Soldiers interacting with technology will provide instructions and direction (i.e., command) as a means for control of unmanned assets to accomplish a particular task or set of tasks. Therefore, we will call the interaction of Soldiers with robotics assets as "direction and control." What we want to emphasize here is the potential and anticipated change from Soldiers "operating" technology, to Soldiers directing and interacting with the technology, in many ways similarly to how Soldiers interact with one another.

Prior, current, and future direction and control of unmanned and robotic assets rely on the foundation of three main relationships: human-robot ratio (number of Soldiers assigned responsibility for, or interaction with, an asset or assets), spatial relationship (distance and direction between or among Soldier(s) and asset(s)), and the authority relationship (defining roles of team members). These three relationships are not new concepts. For example, Burke and colleagues (2004) discussed the importance of these relationships as they can impact the overall team's workload, communication, and situation awareness within a mission. Here we address these three relationships in relation to direction and control of technology, whereby the human-robot ratio is related to the span of control; the spatial relationship is related to both physical proximity as well as operational proximity; and the authority relationship is changing from Soldiers as operators of the tool-based role for robots being replaced with a team-based structure of Soldiers and robots.

Span of control. Span of control has its roots in business management, and is often considered to be the number of subordinates reporting to a supervisor (Urwick, 1956). In the context of robotics and autonomous systems, this can be considered as the number of robots for which an individual person is responsible. There have been a number of studies on this topic (see, for example, Chen, Durlach, Sloan, & Bowers, 2008; Crandall et al., 2005; Wang, Lewis, Velegapudi, et al., 2009). In discussions of human-robot interaction, the span of control is often represented in terms of a ratio: *m*(number of humans)*:n*(number of unmanned or robotic systems). So, *1:1* would represent a relationship of one Soldier to one asset. It would also be possible to have a span of control of multiple people to one system, such as multiple humans needed to operate the system, which could be represented at *m(2+):1* (e.g., for an air system, people to launch, pilot, and land; for a ground system, a person to operate and someone for local security). Some of the studies on the number of robots that can be controlled by a single human are interested in the question of the optimal *n* for the span of control, *1: n*, (one human to *n* unmanned systems). However, safety constraints on current systems (specifically with applications in search and rescue) recommend a 2:1 ratio for unmanned ground vehicles (UGVs), 3:1 ratio for unmanned aerial vehicles (UAVs), and 3:1 for mixed cooperative UGV-UAV teams (see Burke & Murphy, 2007; Murphy, Griffin, Stover, & Pratt, 2006). Ultimately, however, there will networks of both humans and unmanned systems with multiple people interacting with multiple robots. It will be critical to understand the implications for performance and design as the span of control changes from *1:1* or *1: n* to an *m:n* network. Figure 1 provides an illustration of the various forms of human-robot ratios and span of control.

1:1
One-to-one

1:*n*
One-to-many



m:1
Many-to-one

m:*n*
Many-to-many

Figure 1. Illustration of human-robot rations and span of control, including 1:1, 1:*n*, *m*:1 and *m:n* ratios.

Spatial relationship. Here we discuss the spatial relationship between Soldiers and robots in terms of both physical proximity to the robot, as well as operational proximity. The operational context often dictates the physical proximity of Soldier to robot, ranging from on-board (e.g., personnel transport), to nearby (e.g., bomb disposal), to across the globe (e.g., surveillance mission), to name a few. This proximity can influence the perception of the networked team in relation to the mission goals, function allocation related to roles and expectations among Soldiers and robots, and trust development (see also Bainbridge, Hart, Kim, & Scassellati, 2008). We refer to operational proximity in terms of the "distance" from the command structure to the asset(s) for receiving (and sending) information. The "distance" can be thought of as the layers or nodes of the network and the organizational structure that must be navigated to convey information from one person/system to another. With the increasing amount and complexity of technology and communication within network-centric operations including new opportunities for direct communication within networks between individuals and assets, concepts of operational proximity may be changing. For example, in multi-layered hierarchical organizations, there are intervening levels between the top and subordinates – a message from the top must be conveyed through each successive layer of the hierarchy. However, in networked organizations, there can be direct connections among levels. While such direct connections may not be used, and not intended to be used by doctrine or convention, it remains that the direct connections *could* be used, thereby changing the operational distance once maintained. Therefore, while physical proximity may not change with network-centric operations, operational proximity may change substantially.

Authority relationship. The U.S. Army Research Laboratory (ARL) Autonomous Systems Enterprise's vision for the future is to enable effective Soldier-robot teaming. When we think of a team, we usually think of a small unit of Soldiers who perform tasks to accomplish a goal. The team usually has tools to help accomplish that goal. Tools are usually conceived as assets that are used to extend operator capabilities. In the case of a mobile tool, such as a teleoperated robot, the operator will deploy and retrieve, shape and managing the robot activities, including monitoring status and ensuring adequate operation, such as camera feeds. The operator will perform these tasks based on what the team needs are to accomplish the goal. Tasks and goals may be dynamic, with new commands received from the command chain. The team's tools may be used in different ways (or not used at all) as the tasks and goals change. In this concept of a team, there are assets/tools to be used, with the human teammates making decisions on the tool use. According to the Defense Science Board "Report on Autonomy" (2012), unmanned systems are already having a significant impact on military operations and warfare, with the primary value lying in extending human range and capabilities.

In the future, however, we anticipate the tools and assets becoming more intelligent and capable of decision making, as well as autonomous, self-directed action. The assets, formerly only tools, may have sufficient capability to become teammates (see also Phillips, Ososky, Grove, & Jentsch, 2011; Schaefer, 2013). As the progression from tools to teammates occurs, there will be a number of new considerations to be made, for both the human members of the teams as well as in the design of the evolving robotic asset teammate. We also know that, by their very nature, such systems will be part of the network-centric environment. Messages to and from the autonomous systems will be send via networks; such messages could be between machines or between humans and machines. Therefore bi-directional communication will be of great importance to the development of future Soldier-robot teams.

To more fully understand the goals and roles of these future Soldier-robot teams, we draw from the larger research pool on effective human teams (see Cannon-Bowers & Bower, 2011; Mathieu, Heffner, Goodwin, et al., 2000; Mesmer-Magnus & DeChurch, 2009; Rouse, Cannon-Bowers, & Salas, 1992; Salas, Rozell, Mullen, & Driskell, 1999; Salas, Stout, & Cannon-Bowers, 1994). In particular, the work by Salas and colleagues (2005) suggests that features of effective human teams include the core of: team leadership, mutual performance monitoring, team orientation, back-up behavior, and adaptability (see also Figure 2). Required elements of effective human teams that support the core activities include closed loop communication, mutual trust and shared mental models. Later in this paper, these required elements are discussed in terms of the research currently being conducted to support the development of effective Soldier-robot teams.

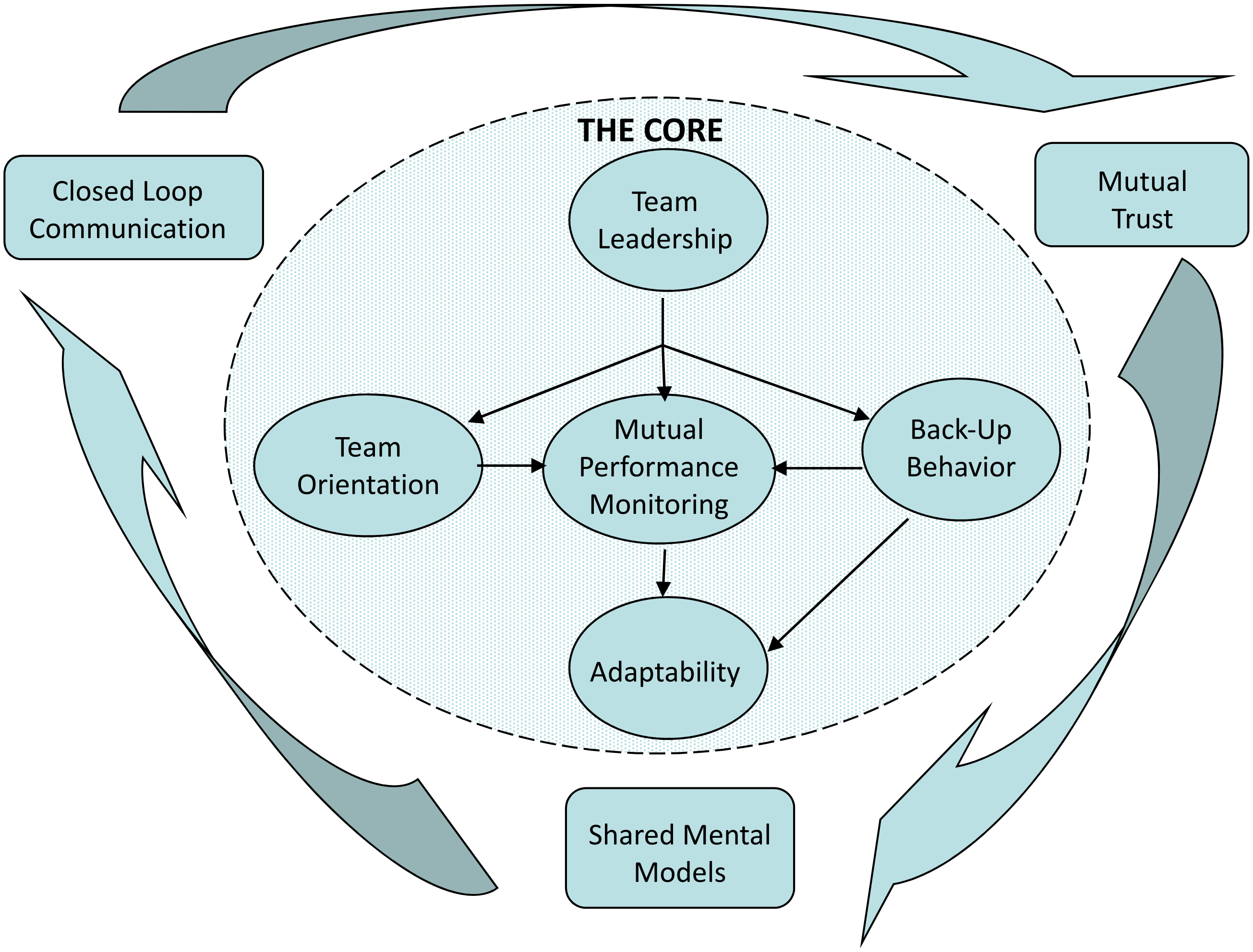


Figure 2. Important elements of effective team performance (adapted from Salas, Sims, & Burke, 2005)

Current Capabilities, Near-Term Developments, and Future Concepts

We can also think about capabilities in terms of current systems, near-term developments, and future concepts. Current systems are those today: for the U.S. Army, the ground robot systems are primarily controlled by teleoperation, with little or no autonomy. Near-term developments are those technological advances on the brink of being realized. Future concepts are the long-term vision, and in many ways represent what capabilities are desired in the future. The future vision of military robots is one in which they will possess the capabilities that will allow them to serve as team members alongside Soldiers, working to achieve common goals (e.g., small unit military fire teams; Army Research Laboratory, 2011). Robots will be expected to move dynamically within their team, maintain mission and situation awareness, understand salient features of their environment, and proactively share information with their human companions (e.g., ferry supplies, search out and interpret intelligence for Soldiers, make critical decisions, guard roads and supplies, and possibly even engage in combat, Carafano, Gudgel, & Kochems, 2008).

Because we are particularly interested in the relationships between Soldiers and intelligent autonomous systems in network environments, there are some basic research areas that will be essential in developing and implementing *useful and used* systems for military operations. Many have argued that the most significant challenge for successful collaboration between humans and robots is the development of the appropriate levels of trust (see Desai, Stubbs, Steinfield, & Yanco, 2009; Groom & Nass, 2007; Hancock, Billings, Schaefer et al., 2011). Until trust between a human and a robot is appropriately established, robotic partners will continue to be underutilized, unused, or neglected altogether. And it is with this neglect that there is little to no opportunity for trust to begin to develop (Lussier, Gallien, & Guiochet, 2007). Thus, it is the presence, or in some cases the absence, of trust that impacts relational outcomes such as attitudes, overt and covert behavior, and perceptions (Dirks & Ferrin, 2001). Further, the presence, growth, erosion, and extinction of trust have powerful and lasting effects on how each member of any shared relationship behaves and will behave in the future (Hancock et al., 2011). Therefore, two research areas that will be focused on in this paper are Soldier-robot trust and communication. Transparency is a third area that is conceptualized as the bridge between trust and communications. These areas will be explored in the following sections across the current systems, near-term developments, and future concepts.

CURRENT SYSTEMS

The current state of trust research has provided a strong theoretical foundation for understanding the importance of trust development and trust calibration as it applies to current and future Soldier-robot teams (see Hancock et al., 2011; Hoff & Bashir, 2014; Schaefer, Billings, Szalma, et al., 2014). Essentially, trust serves to increase understanding (i.e., reduce uncertainty), and enable individuals to anticipate, predict, and perhaps even avoid situations which are typically characterized by high levels of risk, vulnerability, uncertainty, and the need for interdependence (Bhattacharya, Devinney, & Pilluta, 1998). However, the less an individual trusts a robot, the sooner he or she will intervene in its progress toward task completion, thus mitigating any benefits of the robot (see de Visser, Parasuraman, Freedy, Freedy, & Weltman, 2006; Steinfeld, Fong, Kaber, et al., 2006). Therefore, the current state of the literature has primarily focused on the development of trust.

Trust and the Operator

The primary type of interaction with current fielded military robots can be most accurately described as operator interaction. Scholtz (2003) describes the operator as a person that determines if robot actions are being carried out correctly and if the actions are in accordance with the longer term goal. Operators can directly intervene to correct inappropriate behaviors. Most often operators take direct control or teleoperate the robot through an operator control unit (OCU). A second type of interaction that is often discussed in relation to current systems is supervisory interaction. Scholtz describes a supervisor role as someone who monitors robot(s) actions and controls the overall situation and plan. Within these roles, trust is often thought of in terms of a one-to-one primary relationship where the individual receives data directly from the robot. In many cases, the robot offers an extension of the Soldier's physical reach by providing additional sensory data that can enhance awareness of the operation space or situation. This structured relationship exemplifies the anticipated use of a robot as a tool.

Since this is the current state of interaction, it is the area of human-robot trust development that has been most comprehensively studied. In a formal meta-analytic approach, Hancock and colleagues (2011) formulated and formalized a triadic model of human-robot trust thus highlighting the importance of the human-related, the robot-related, and the environmental factors that influence trust development. More specifically, that work found that i) despite the theoretical importance of trust, it is still a relatively new field of study that requires more empirical research in order to more fully understand how trust develops; ii) within operator and supervisory interactions, the robot's behaviors and the reliability of its actions are most studied, and have been found to be key to trust development; iii) even within these types of interactions there is some degree of interdependency and team collaboration with the robot; and iv) there are many gaps in the literature that explore the human element and importance of communication to trust development. More recently this model has been updated through a meta-analysis of the larger field of human-automation trust (see Figure 3).

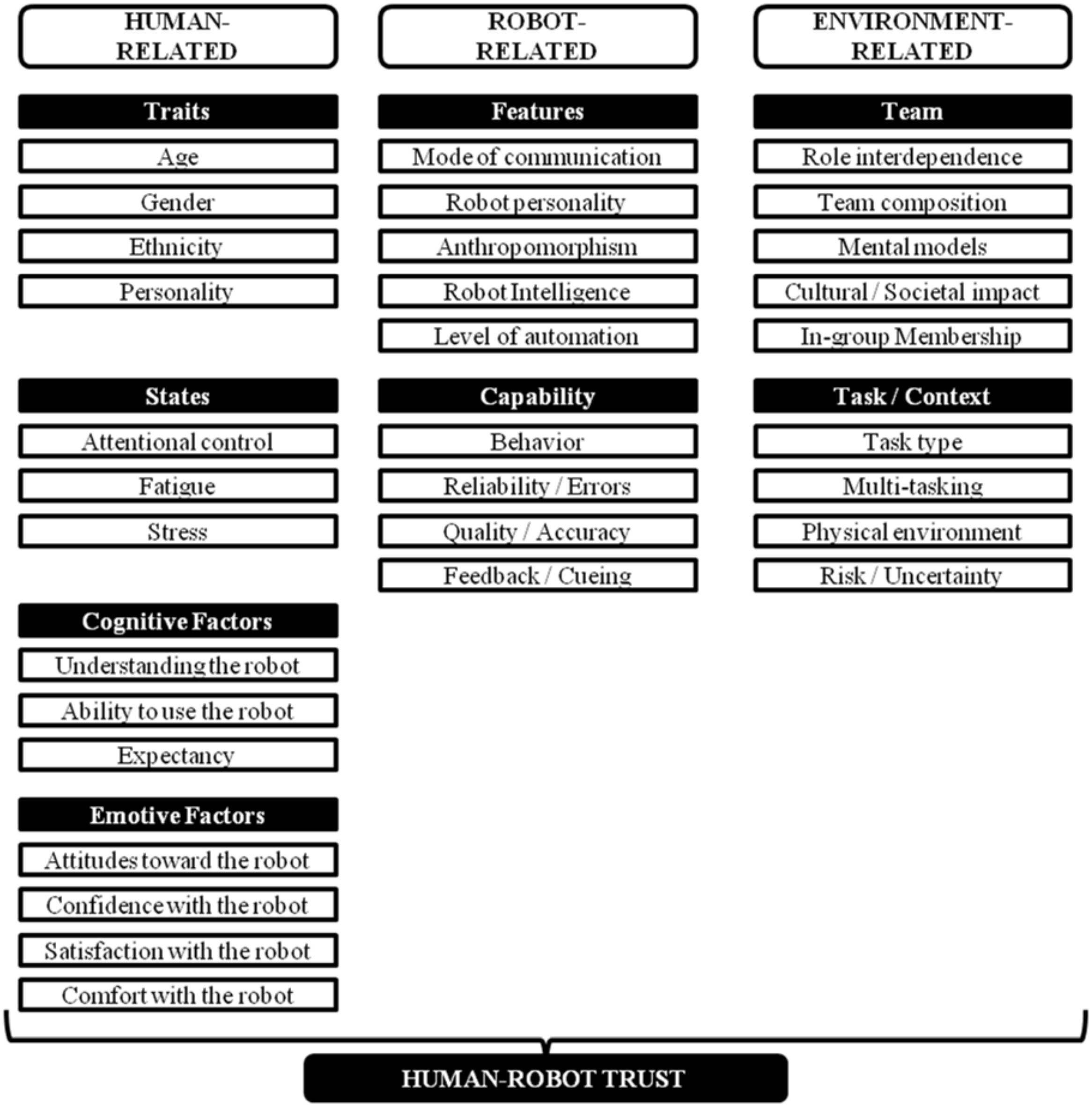


Figure 3. The updated Three Factor Model of Human-Robot Trust following review of other human-entity domains (adapted from Hancock et al., 2011 and Schaefer et al., 2014).

Communication, Transparency, and Trust

Human-robot interaction and human-automation interaction literature have both identified the importance of reliability, predictability, and dependability of a system on trust development and performance across multiple domain areas. These include mixed-initiative combat teams (Ogreten, Lackey, & Nicholson, 2010), route planning (de Vries, Midden, & Bouwhuis, 2003), decision aids (Ross, 2008), target detection and combat identification (Chen & Terrence, 2009; Wang, Jamieson, & Hollands, 2009), and fault management (Moray, Inagaki, & Itoh, 2000). However, additional research is beginning to show the importance of effective bi-directional communication and transparency on trust development.

Research has identified the importance of communication accuracy (e.g., adaptive cruise control system's ability to effectively communicate the status, Stanton, Young, & Walker, 2007; a military robot's ability to accurately detect targets while screening the back door of building; Schaefer, 2013) and availability of information (e.g., adaptive cruise control, Seppelt & Lee, 2007). In addition, different types of cueing systems can impact trust development, but may be person or task dependent. For example, spatial cueing was beneficial for all age groups in detecting threat objects during a screening task, while text-cueing only helped young adults (Wiegmann, McCarley, Kramer, & Wickens, 2006). The effect of the type of alarm on trust development appears to be task dependent. Gupta and colleagues (2002) found no difference in trust for type of alarm in collision avoidance system; while Donmez et al. (2006) found that drivers trust visual alarms more than auditory alarms for distraction mitigation. More recently, studies are beginning to identify the importance of communication on trust development during human-robot interaction.

Recent research has shown that transparency in both behavior and communication can be a critical component building trust in human-robot teams (Barnes, Chen, Jentsch, et al., 2014; Chen & Barnes, 2014; Ososky, Sanders, Jentsch, et al., 2014; Sanders, Wixon, Schafer, et al., 2014). However, limitations in the process in which autonomous systems are able to convey information to users currently restricts this level of transparency. Unlike their human counterparts which communicate in a number of both explicit (e.g., speech, written communication) and implicit (e.g., body language, facial expressions) ways, autonomous systems are heavily dependent on using explicit communication and cannot currently rely on implicit communication to convey information on meaning. Thus, the transparency of a robot's actions, calculations, and decision making becomes even more important factors to building trust, especially in Soldier-robot teams. Additionally, transparency can also contribute significantly to creating shared mental models, which has been shown to be an important contributing factor in increase team performance and situation awareness (Mathieu et al., 2000; Rouse et al., 1992; Salas et al., 1994).

Other research looking at how transparency affects the attribution of blame found that the more transparent a system was, the less willing users were to blame that system for failures, but rather blamed their co-workers (Kim & Hinds, 2006). Interestingly, this research also showed that regardless of the amount of transparency, more autonomous systems lead to users shifting blame from themselves onto either the autonomous systems or co-workers. This suggests that transparency in autonomous systems might provide better understanding of autonomous system functions but does not encourage accepting greater levels of responsibility on to the user. This is important to point out as an issue for human-robot teams seeking to develop more human-human team traits. In future research on trust and transparency, responsibility should be counted as a major contributing factor to team successes and failures.

Transparency and Operator Control Units

Some research that is making an effort to increase transparency with current systems is in the area of operator aids. An experiment looking at the use of visual overlays on robot control screens, showed encouraging results (see Evans, 2013; Evans, Hill, Woods, & Pomranky, 2015). In this study, operator aids, in the form of the visual overlays, were designed to provide information to the controller about what an autonomous system was 'seeing,' as well as its intended actions.

Figure 4 provides a visual representation of the Warfighter Machine Interface (WMI 3D) operator aid.

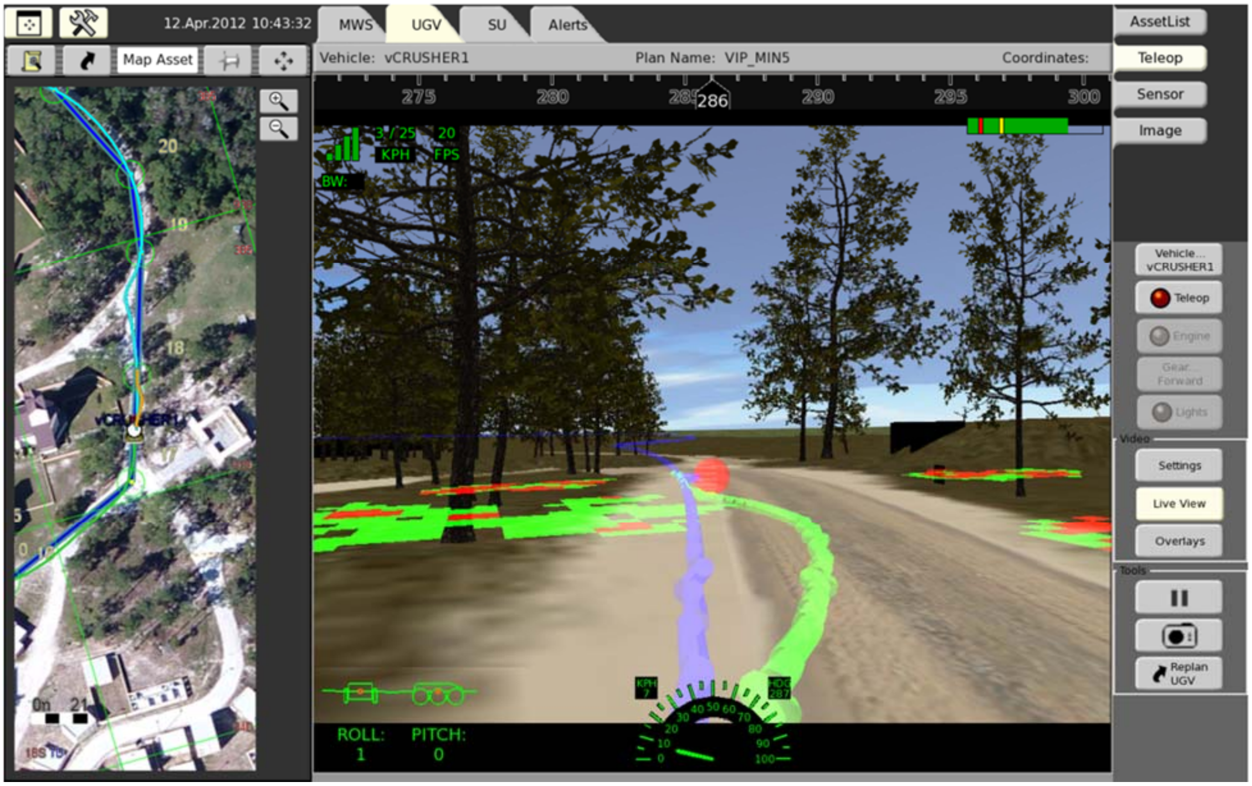


Figure 4. An example of the original WMI 3D interface showing both the Short Term Planner (green line) and Long Term Planner (blue line) operator aids (Evans, 2013).

Results of this study showed that the use of operator aids, providing information about what the autonomous systems where planning and why, allowed users to engage in tele-operation control less often and for shorter durations. This finding was attributed to users having a greater ability to understand and predict future autonomous system behaviors and feeling less need to interact to due to misunderstanding in system behavior. These types of findings also support the transition to interdependent Soldier-robot operations.

NEAR-TERM DEVELOPMENTS

The near-term developments have begun to identify major considerations related to interdependent teaming. As robots take on roles of integrated team members (presumably without human-level intelligent-competence), the issue of trust becomes a major concern (Hancock, Billings, & Schaefer, 2011). Trust impacts the degree to which a human teammate is willing to accept contributions from a robot (e.g., sensory data, information to assist in decision making, suggestions for courses of action); thus, the human may potentially fail to take advantage of the inherent benefits of the robotic system (Freedy, de Visser, Weltman, & Coeyman, 2007). For this reason, trust is especially critical when it comes to decision making in high-risk environments such as military combat missions (Park, Jenkins, & Jiang, 2008). Further, a human's trust in a non-human teammate is a necessary requirement to ensure that any functional relationship will ultimately be effective regardless of domain, environment, or task.

Trust and Networked Team

Soldier-robot relationships are beginning to change from the predominant operator interactions, where the robot fulfills a tool-based role, to a more interdependent team-based role. It is the technological advancements of machine intelligence that lends itself to increased decision making capability and robot autonomy. It is with this transition in mind that we move into near-term developments as it relates to trust and the networked team.

To revisit the changing interaction roles first discussed by Scholtz (2003), there are two additional roles that are beginning to be more readily discussed in literature: peer interaction and bystander interaction. Scholtz describes peer interaction as a communication-based interaction in which teammates may give commands within the larger goals or intentions. Within a military operation we visualize this interaction as one between the robot and the ground team. However, within that same environment there may be a level of what Scholtz called bystander interaction, where the individual has no information about the goals or intentions of the robot. More recently Beer, Fisk, and Rogers (2014) further defined various levels of interdependency and interaction that occur with various degrees of robot intelligence and autonomy.

This change in interaction roles is still an area that requires additional exploration as it directly impacts how trust is developed within these new interaction roles. Further, the advancements in robot intelligence and autonomy are changing the perception and use of a robot merely as a tool within network-centric operations (see Schaefer & Cassenti, 2015). In the near-future we will begin to see robots being more readily integrated as part of the communication network or even as part of the social network (Figure 5). Yet despite the effectiveness of the operational capabilities of the robotic system, it is trust that directly affects the willingness of people to accept robot-produced information, follow the robot's recommendations, accept the robot's actions, and thus benefit from the advantages inherent such in robotic support (Chen & Terrence, 2009; Freedy, de Visser, Weltman, & Coeyman, 2007).

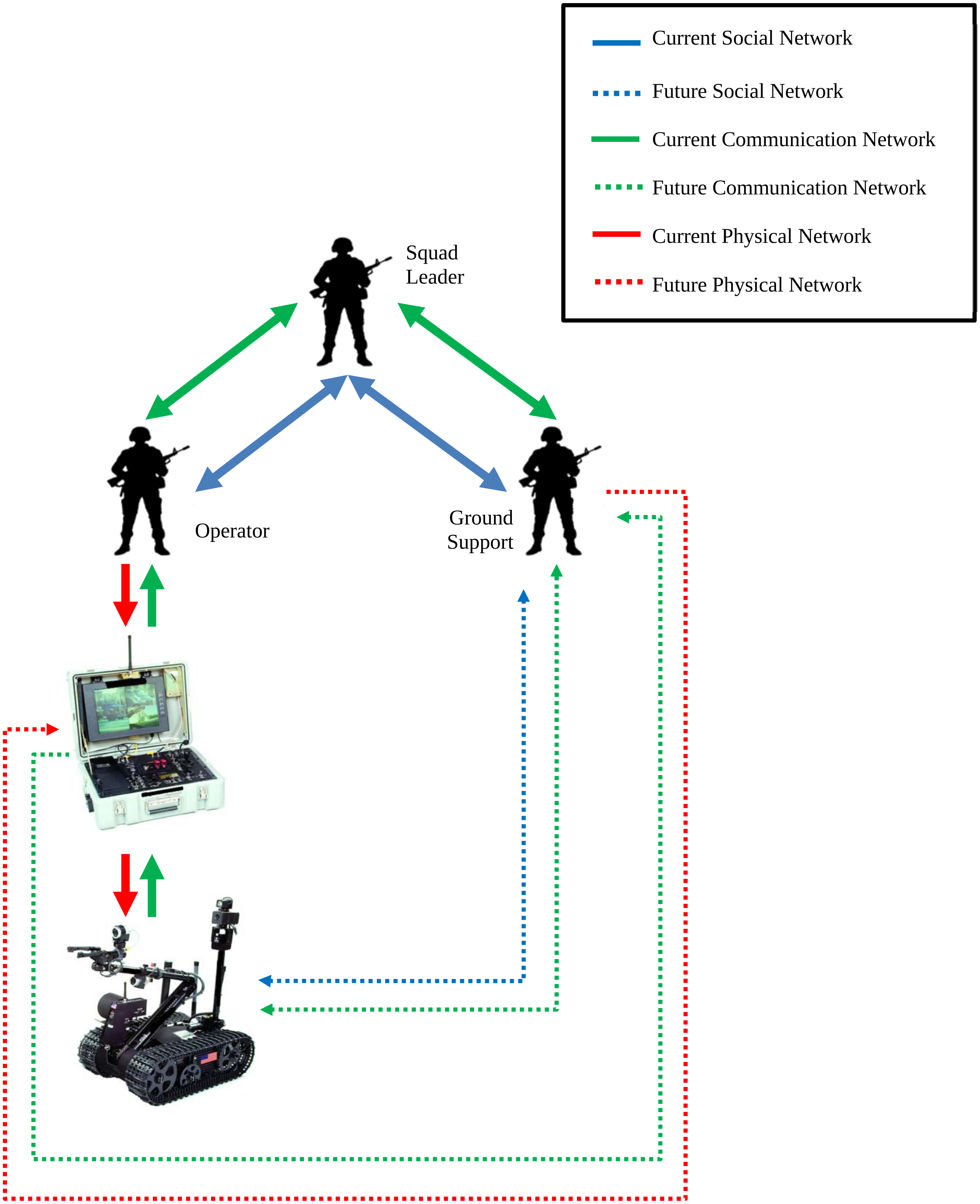


Figure 5. Visual representation network-enabled operations for current Operator and Supervisor Interactions, represented by solid lines, and possible future Peer Interaction with the ground support team, represented by dotted lines (adapted from Schaefer & Cassenti, 2015).

In the near-term we begin to assess trust and networked team. This extends beyond just the primary trust relationship discussed in the prior section, to discuss the possibility of distributed trust. The theoretical concept of distributed trust looks beyond the 1:1 team structure to start to include the larger team. In a concept paper on distributed trust, Oleson and colleagues (2011) suggest that there is a link between communication and distributed trust for larger than one-to-one teams. More specifically there are different levels of trust that occur across the team structure: Primary Level Trust (trust between entities that receive direct communication from other team members), Secondary Level Trust (trust that may be present among team members across all lines of indirect communication), and even Tertiary Level Trust and beyond (more complex interaction between multiple team members). This concept of distributed trust takes on a more prominent importance as we begin to more fully integrated robotic systems into these network-centric operations, as the primary, secondary, and tertiary relationships begin to change as the roles and access to information changes.

Near-Term Developments in Displays and Controls

When discussing near-term developments for displays and controls in the U.S. Army, much of the focus is transitioning to becoming more ‘mobile.’ A recent article points out how strides are being made to further the use of 4G networks on battlefields, substantially increasing the usefulness of Smartphone and tablet computers (Walker, 2014). Figure 6 provides an example of a Smartphone display.

Figure 6. An example of the type of OCU Smartphone size display which could be common in the future military.

The Department of Defense (DoD) has made it clear that the use of mobile devices and the associated applications (app systems) are very intriguing as possible tools to meet U.S. military needs (Agre, Gordon, & Vassiliou, 2014). The U.S. Army has already been developing apps in areas like training (Tucker, 2010), management of post traumatic stress disorder (Kuhn, Greene, Hoffman, et al., 2014), and route planning (Hebeler, McKneely, & Rigsbee, 2012), among others. While this suggests that Soldiers can have a multi-function low cost tool at their disposal, there will still be challenges associated with the use of handheld devices. One of these issues will be display screen ‘real estate’ – the amount of space available on a particular screen size for displaying information. While visual displays will be shrinking, more information will be available to Soldiers than ever before. Therefore, the graphical user interface design displayed on the device screen and its usability will be critical to mission success. Current concepts for robotic operator aids (i.e. obstacle map and travel planner; Evans, 2013) will need to be re-evaluated and potentially redesigned with smaller display screens, such as those available on mobile devices (in comparison to larger, desktop-type display screens), in mind.

At the U.S. Army Research Laboratory, ongoing work seeks to gain a better understanding of the usefulness of commercially available screen designs and applications. One question of interest is how much information can reasonably be expected to be perceived and understood by humans with limited time 'heads down.' This question is particularly important when we consider that as mobile devices become used more by Soldiers for operational needs, so to do the dangers of becoming absorbed in the mobile displays rather than maintaining local situation awareness. While many successful, intuitive, and useful apps have been developed for the commercial market, the commercial operational environment is quite different from the military operational environment. More needs to be known about mobile devices as controls for robotics, considering performance and emersion, as well as transparency and trust. It is important that each of these perspectives is considered as handheld, mobile devices are further incorporated into everyday military operations. By creating easy to use, more naturally communicating interfaces, the expectation is that Soldiers will be able to command robots agents with more ease, precision, and trust. These are all critical elements of developing a user experience encouraging supervisory control rather than the need for constant interaction required in most teleoperation controlled systems available currently.

FUTURE CONCEPTS IN COMMUNICATION AND CONTROL

As stated in the Army Operating Concept 2020-2040 (2014), "[w]hile the development of advanced technologies is important, the integration of these technologies into Army units and training maximizes the potential of any technology." (p. 34). One of the key technology focus areas discussed in document is "autonomy-enabled systems" (p. 37), which will be deployed as force multipliers to extend and enhance Soldier and unit capabilities. The long-term vision of effective Soldier-robot teaming with autonomous systems includes changing the paradigm from an operator interacting with technology through a visual display and keyboard to natural, intuitive interactions. Such a paradigm shift conceives of using head's down, visual displays only when necessary to obtain visual information.

Current research addressing the future goal of communications and control beyond current visual displays is in the area of multi-modal capabilities. Multimodal communications includes using more than the visual mode for interaction; it includes multiple modes such as speech, gesture, and tactile communications. Speech is particularly important, since it is a primary mode of communication among people. Certainly, single word speech commands are within current capabilities of interacting with robots. Structured language interaction, where there are some constraints on what is said, and how it is said, will be near-term developments. The future, long-term goal of natural language dialogue between humans and robots is still being pursued (Kollar, Tellex, Roy, & Roy, 2010; Marge, Pappu, Frisch, Harris, & Rudnicky, 2009; Walter, Antone, Chuangsuwanich, et al., 2014). Natural speech interaction will go a long way in achieving communications that are more natural and less cognitively burdensome.

A second area of multimodal communications is gesture. Gestures can be used as simple signals to convey single, limited commands, such as gestures used in military (described in the Department of the Army Field Manual (FM) 21-60, *Visual Signals*, 1987). Gestures could also be as complex as American Sign Language; for example, Stokoe (1978) has analyzed ASL from a linguistics point of view. Gestures are being explored as a means of communication with robots (Barber, Reinerman-Jones, & Hudson, 2013; Lackey, Barber, Reinerman-Jones, Badler, & Hudson, 2011; Suarez and Murphy, 2012). Combined speech and gesture could be a powerful and expressive means for natural communication.

A third communication modality being explored is the tactile mode. Tactile interfaces take advantage of human sense of touch, using small tactors, or vibration sources, that are used to associate particular vibration signals to a meaning. The vibration can be thought of as similar to a vibration signal from a cellular phone. For the cellular phone, the vibration means the phone is ringing, or a message has arrived. Similarly, a tactile interface associates a vibration, or multiple vibrations, to particular meaning. For example, a single vibration on a tactile interface belt, circling the waist, can indicate a direction to take. Multiple, simultaneous tactile signals or a sequence of signals, can indicate other meanings, such as “halt.” Tactile interfaces have shown the ability to convey self-navigation information (Elliot, van Erp, Redden, & Duistermaat, 2010) as well as signal simple alerts (Self, van Erp, Eriksson, & Elliott, 2008). More recent research in tactile displays has expanded the use for self-navigation to also include robotic asset monitoring capabilities (Pomranky-Hartnett, Elliot, Mortimer, et al., in manuscript).

Another aspect of future communication between humans and robots will be to take advantage of all those communication streams that people use to understand each other, in addition to speech, gesture and tactile interfaces. People use body language like shrugs or various facial expressions to convey meaning, while non-speech vocalization, like shouts, grunts, whistles, can communicate information. Therefore, the way in which robots can sense that kind of communication, understand its meaning across different contexts, and use the information to make decisions are all areas for research for future implementation.

Underlying all of these future means of communication is the thought that the robot will have the intelligence needed to establish “common ground” with the Soldiers team members. This will include shared mental models, shared goals, and a shared understanding of the world so that communication and action are mutually understood and expected. Referring back to Figure 2, the creation of these shared mental models are critical to achieving effective team performance and calibrating trust as these capabilities and interaction modes are developed for future network-centric operations.

CONCLUDING REMARKS

In this paper, we have described the way in which interaction and teaming between intelligent, autonomous systems and Soldiers is changing within a network-centric environment. Interactions are moving from current systems, which are directly controlled teleoperated tools, to future systems, which are anticipated to be more a part of an interdependent Soldier-robot team. One key aspect that will impact individual and mission performance includes how autonomy is developed and implemented, including the future goal of shared perception and understanding between robots and Soldiers. A second key aspect will be the communications between Soldiers and robots, with a vision of changing the paradigm from heads-down, visual display-based communications to more natural intuitive means such as speech and gesture. Finally, the relationship between communication and shared mental models, ties directly into the development and calibration of trust, which together are critical to enabling effective Soldier-robot team performance.

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