Chapter 16 – US-3: INTELLIGENT AGENTS AS SUPERVISORY ASSETS FOR MULTIPLE UNINHABITED SYSTEMS: ROBOLEADER

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16.1 DATES

2009 – 2011.

16.2 LOCATION

Aberdeen Proving Ground, MD, USA.

16.3 SCENARIO/TASKS

Urban reconnaissance.

16.4 TECHNOLOGIES EXPLORED

Intelligent agent to coordinate a team of ground robots for urban reconnaissance tasks.

16.5 HUMAN FACTORS ISSUES EXPLORED

16.5.1 Introduction

Future military operations will be complex and diverse. U.S. forces and its allies will be engaged simultaneously on a number of fronts under different combat conditions while fighting adversaries using a variety of tactics. Because of the changing demographics, many of our engagements will be in urban areas with entrenched adversaries who do not have to defeat us; instead they need only to out-wait us [1]. These conflicts will require the Army to put Soldiers "in harm's way" and in the process encourage adversaries to use any means at their disposal to outlast our resolve. One possible solution will be the implementation of robotic systems that can replace Soldiers on the battlefield increasing our forces' survivability and durability. Eventually these systems will be able to operate 24/7 in difficult terrain testing the Soldier operator's ability to supervise these assets while conducting normal operations. Also, the possibility of a robotic battlefield creates a number of human factors as well as ethical issues related to non-human intelligence conducting combat missions [2],[3]. One obvious issue is that the proliferation of intelligent systems could easily overwhelm the current force's ability to adequately supervise these systems. Hundreds of Uninhabited Vehicles (UVs), both aerial and ground, will share the

battlefield with hundreds of manned systems and conduct numerous missions concurrently. In these situations, the military will not be able to afford the manpower to control individual systems; instead, future missions will require single operators to supervise multiple systems. This, in turn, will necessitate some degree of UV autonomy. Unfortunately, increases in autonomy will present its own set of problems, including tunnel vision, misuse and disuse of automated systems, complacency, and loss of situation awareness [4],[5]. More germane to our current discussion, increases in autonomy will not overcome the human's span of apprehension limits related to monitoring multiple systems at the same time [6],[7].

Researchers have proposed a number of solutions to the potential issues of a robotic battlefield, such as setting up a UV call center in which robots will query the human operator only when there is a problem. The operator will make the necessary adjustments but will not be required to monitor robots continuously [8]. The obvious problem with this solution is that it assumes that the UV will be able to self-diagnose its own problems; additionally, the number of operator–robot interactions is expected to increase exponentially during the heat of combat, making the call center ineffective during the most critical time periods. As a potential safeguard, a number of researchers have suggested algorithms that share control responsibility among robots and humans as a function of either the robots' behavior or the operator's cognitive state. Closely aligned concepts involve play-book solutions that permit the operator to insert pre-programmed algorithmic solutions that control robots during difficult mission segments [9]. This generic class of adaptive systems is designed to keep operators in the decision loop while keeping the overall supervisory burden within efficient cognitive limits [9]-[12]. However, while this approach mitigates problems during high workload, it does not overcome cognitive limitations when the number of human–robot interactions surpasses human cognitive capacity [6]. We will examine two approaches that directly address the many-to-one problem:

a) Distributed intelligence using swarm technologies; and

b) Centralized intelligence using an intelligent agent as an intermediate supervisor.

The Tech Demo (RoboLeader) demonstrates the dynamics of an intelligent agent interacting with the human operators to coordinate a team of ground robots conducting an urban reconnaissance mission. In artificial intelligence, an intelligent agent is typically defined as "an autonomous entity which observes and acts upon an environment and directs its activity towards achieving goals" [13]. This definition covers a variety of possible uses for intelligent agents, from swarms with individual agents of limited intelligence that evince sophisticated behaviours holistically, to agents that respond to particular tasks in a manner that emulates human intelligence. As a contrast to RoboLeader's theoretical underpinnings, we will initially discuss swarms, emphasizing recent research from the Army Research Laboratory (ARL; Figure 16-1). The purpose of discussing swarms will be to delimit the theoretical possibilities for supervising multiple UVs in order to set the stage for our discussion of RoboLeader.

Figure 16-1: Swarm Display [16].

Swarm technologies are a special type of distributed intelligence wherein each component has a limited capacity to respond to its environment and the intelligence resides within the combined behavior of the group. Modeling swarms is an example of bio-inspired engineering using techniques that mimic collective behaviors of organisms such as of birds, ants and bees. Scientists have modeled swarm behavior making simple assumptions about the rules that individual members of the swarm use to permit the group to obtain its desired end states. Rules can be such simple actions as: stay close to your neighbor, avoid collisions, and move in the same direction. For example, Craig Reynolds developed an algorithm describing flocking behavior, including obstacle avoidance, to mimic avian flight paths accurately [14]. His Boids program was so successful that it was used to develop flight animations in the *Bat Man Returns* movie in 1992. A curious aspect of swarm behavior is that no single agent is in charge making the Swarm invulnerable to an individual's poor decisions. For example, in the biological domain, scout ants will go off in many directions and foragers will count those coming back in a particular direction to decide in which direction to find food for the colony [15].

More pertinent to military problems is the work that ARL researchers have conducted using swarm methods to control sentry robots for convoy protection (Figure 16-1) [16]. The robots use rules similar to the ones

instantiated for flocking behaviors to form an ellipse around the convoy, with individual robots venturing neither too close nor too far from the convoy. The algorithm had to be robust enough to account for unexpected weather, obstacles, etc., in the convoy's path. Using a simulation program with artificial obstacles, the robots were able to stay within the prescribed distance of the convoy 85% of the time. The problem with swarm technology is that swarms are most useful for simple problems wherein adaptation to novel conditions is not an important part of the problem set. Also, swarms are difficult to control because they are essentially interacting components with no clear means of supervisory control [17].

For more complex problems, hierarchical agent systems are being designed with agents that have specialized intelligence embedded within multi-layer architectures. The individual agents have specific tasks and a means of communicating with other agents. The ability to divide task complexity between senior (more capable) agents and specialized (less capable) ones allows hierarchies to adjust to greater complexity and to better adjust to change. The disadvantages are that as hierarchies become more complex, the algorithms to control them also become more cumbersome, and even then, agent hierarchies are still challenged by truly novel situations. Furthermore, the more levels involved and the more entities that need to be controlled, the more likely it is that communications among agents will become a serious problem. Carnegie Mellon University (CMU) developed algorithms using various bidding techniques in order to assign agents specific tasks. Bidding for tasks in the same neighbourhood reduced the size of auctions and it also reduced the distance that each agent was required to travel to complete its mission. In general, three levels of hierarchy were found to be the most efficient network size in order to trade-off number of agent specialties with network complexity [18]-[20].

Agent technologies with military import have been demonstrated for a number of realistic applications. For example, the L-3 Corporation and CMU used agents to successfully control multiple Unmanned Aerial Vehicles (UAV) with Received Signal Indicator (RSI) sensors to locate targets cooperatively during high fidelity simulations [21]. Researchers for the Canadian Defence Research and Development Laboratories (DRDL) demonstrated the utility of agent hierarchy technology for UAV control in a more complex simulation environment [22]. Hou and his colleagues [22] used senior agents directing working agents who in turn directed junior agents. Their simulation demonstrated agents in concert with the operator, planning multiple UAV missions, navigating UAVs to the target area, and upon arrival directing sensors to locate the targets. Similar agent technology has been used for cooperative control of multiple UAVs at the German Bundeswehr University in Munich using live UAV demonstrators [23].

16.5.2 Human-Agent Teaming

An important feature of most military-related agent research is that agents are imbued with limited autonomy. Agents can perform specialized functions but authority resides with a human supervisor for safety and tactical reasons [2],[23]. Human-agent teams seem to be particularly effective for open ended missions in which not all events can be pre-programmed (i.e., most combat situations). Successful agent technologies take advantage of the differences between human and agent strengths. Human reasoning has very different characteristics than algorithmic reasoning. Johnson-Laird [24] points out that humans are rational but do not use formal logic in everyday decision making. They tend to structure problems by focusing on only some of the possible logical implications; permitting humans to rapidly but sometimes erroneously solve real-world problems (see for example, Monty Hall problem [25]). On the other hand, using inductive processes, humans are able to visualize numerous possible patterns that would overwhelm current agent technology. Also, we tend to overlook the advantages of consciousness which gives humans an acute awareness of the present and an intuitive feel for future states as well as a sense of purpose [26]. Human intuition is not an inexplicable process but rather it involves matching multiple memory traces with current cues that alert Soldiers to possible

incongruities in the environment. Experts, in particular, are able to pick up on cues that allow them to circumvent detailed analysis [27]. Also, humans can understand and react to situations in terms of overall intent rather than specified objectives. Artificial agents are able to supplement human intelligence by their use of more formal logic and their use of complex optimization algorithms to solve circumscribed problem sets. Agents also reduce workload by being able to attend to multiple functions that would overwhelm Soldiers during the heat of combat. Human-agent teams are especially important in military environments because no set of agents in the foreseeable future will be able to understand the nuanced political and ethical implications facing U.S. ground troops [2],[28].

The purpose of the below research is to better understand how humans and intelligent agents work together effectively as team to engage in military missions wherein Soldiers will be required to supervise multiple UVs during high workload combat missions [4],[29]. RoboLeader is a simple hierarchical system consisting of human operators, intelligent agents that can communicate with both the human supervisor and other agents, and less intelligent agents consisting of multiple UVs (robots) who conduct prescribed missions. The dynamics of the interactions and report of our initial findings will constitute the demonstrations and are described below.

16.5.3 Framework Applied to HFM-170

The purpose of our demonstration is to show the advantages of a hybrid supervisory system with a centralized agent controlling multiple UVs in an urban combat environment. RoboLeader will be contrasted with swarm systems and we will discuss research showing its advantages in controlling up to 8 robots. Past research indicates that autonomous cooperation between robots can improve the performance of the human operators [30], as well as enhancing overall human-robot team performance [31]. The current research paradigm addresses the control structure and interface requirements between the supervisory human operator and robotic agents as number of agents, workload, target mobility, and reliability level vary systemically [32],[33].

16.6 UNMANNED SYSTEMS USED

Simulated unmanned ground vehicles.

16.7 SUMMARY OF ANY NATO COMMUNICATIONS/COLLABORATIONS/ INTERACTIONS

Communications included the HFM-170 community by sharing papers and presentations. Direct interactions were with TNO Netherlands, Air Force Research Laboratory (AFRL) and DRDC Canada. Interactions with Canada include sharing software and concrete plans for joint research on intelligent agents, TNO participated in field experiments at Ft. Benning and AFRL contributed to our voice research.

	Planning/Design	***Execution***	***Analysis***
Communication	*X*	*X*	*X*
Coordination	*X*		
Collaboration	*X*	*X*	

16.8 SUMMARY OF TD RESULTS

16.8.1 Experiment 1

We investigated the effectiveness of RoboLeader, an intelligent agent that could help the human operator control a team of robots, for enhancing the overall human-robot teaming performance. We compared the operators' target detection performance in the 4-robot and 8-robot conditions [32]. The Mixed Initiative Experimental (MIX) Testbed was modified and used as the simulator [34]. The MIX Testbed is a distributed simulation environment for investigation into how unmanned systems are used and how automation affects performance. The Operator Control Unit (OCU) of the MIX Testbed was modeled after the Tactical Control Unit developed under the ARL Robotics Collaborative Technology Alliance (Figure 16-2). This platform includes a camera payload, and supports multiple levels of automation. Users can send mission plans or teleoperate the platform with a joystick while receiving video feed from the camera payload. Typical tasks include reconnaissance and surveillance.

Figure 16-2: RoboLeader User Interface.

Participants were randomly assigned to the RoboLeader group or the Baseline (no RoboLeader) group before their sessions started. Each experimental session had two scenarios, each lasting approximately 30 minutes, in which participants used their robotic assets to locate 20 targets (i.e., 10 insurgents carrying weapons and 10 Improvised Explosive Devices [IEDs]) in the remote environment. There were 4 robots available in one scenario and 8 in the other. The order of scenarios was counterbalanced across participants. When each scenario started, the robots began by following pre-planned routes at which time the operator's task of monitoring the environment and detecting insurgents/IEDs began. The robots did not have Aided Target

Recognition capability; therefore, the participants had to detect the 10 insurgents and 10 IEDs by themselves. There were friendly dismounted soldiers and civilians in the simulated environment to increase the visual noise for the target detection tasks. The participants were told that their objective was to finish reconnoitering the area using their robotic assets in the least amount of time possible. Therefore, when re-planning a route, the participant and/or RoboLeader were required to consider both the effectiveness and efficiency of the new route. In each scenario, there were six events that required revisions to a robot's current plans/route. Once an event transpired, the baseline participants had to notice that the event had occurred, and then they would re-route the robot that was affected by the event. For those in the RoboLeader condition, the RoboLeader recommended plan revisions to the operator, who could either accept the plans or modify them as necessary. In each scenario, there were 5 Situation Awareness (SA) queries, which were triggered based on time progression (e.g., 3 minutes into the scenario). The SA queries included questions such as "which areas have the robots searched?" (participants were instructed to mark the searched areas on a blank map), "which of your robots is the closest to [Area of Interest]", etc. The OCU screen was blank when an SA query was triggered, and only the SA query and the answer box were displayed on the screen.

The study was a mixed design, with RoboLeader (with or without RoboLeader [Baseline]) as the between-subject variable, and the number of Robots used in the scenario (4 vs. 8) as the within-subject variable. Dependent measures included number of targets located and identified, the operator's SA of the mission environment as well as awareness of the status of the individual robots, and the operator's self-assessed workload. A mixed-design analysis of covariance with RoboLeader (with or without RoboLeader) as the between-subject factor and number of Robots (4 vs. 8) as the within-subject factor was used to evaluate the operator's performance differences among the four conditions. Participants' spatial ability (composite score of two spatial tests) and their attentional control survey scores were used as covariates.

Results showed that participants detected significantly fewer targets and had significantly worse SA when there were 8 robots compared to the 4-robot condition. Those participants with higher spatial ability detected more targets than did those with lower spatial ability. Participants' self-assessed workload was affected by the number of robots under control, their gender, and their attentional control ability. Although there was no significant difference in overall target identification between RoboLeader and baseline conditions, there was a 12% reduction in mission completion time for the RoboLeader condition.

16.8.2 Experiment 2

In the first experiment, the simulated reliability level of RoboLeader was 100% (i.e., no false alarms or misses). In Experiment 2, the effects of various reliability levels for RoboLeader on operator performance were investigated [32]. The participants' task, as in Experiment 1, was to manage four robots with the assistance of RoboLeader while searching for hostile targets via streaming video from the robots. The reliability of RoboLeader's solutions was manipulated to be either False-Alarm Prone (FAP) or Miss Prone (MP), with a reliability level of either 60% or 90%. Furthermore, Experiment 2 simulated a multi-tasking environment rather than a dual-tasking environment as in Experiment 1. In addition to the target detection and route revision tasks, the participants had to simultaneously perform a gauge monitoring task and a communication task. Finally, the visual density of the simulated environment was manipulated; there were twice as many entities in the high density environment as in the low density environment. The experiment is a mixed design, with RoboLeader Imperfection Type (FAP vs. MP) and Reliability Level (60% vs. 90%) as the between-subject factors and Visual Density (High vs. Low) of the simulated environment as the within-subject factor.

Participants were randomly assigned to the FAP60, FAP90, MP60, or MP90 group (with 10 participants per group) before test sessions started. The participants were informed that RoboLeader was either FAP or MP

and "fairly but not always reliable" (for the 90% conditions) or "not always reliable" (for the 60% conditions). In the MP scenarios, participants were required to notice and manually edit several routes without the help of RoboLeader. RoboLeader's messages were displayed in the upper left corner (the blue area) of the OCU (see Figure 16-3). As in Experiment 1, participants were told that their objective was to finish reconnoitering the area using their robots in the least amount of time possible while keeping all route edits as close as possible to the original routes. Therefore, when re-planning a route, the participants and RoboLeader had to consider the effectiveness and efficiency of a new route.

Figure 16-3: RoboLeader in a Multi-Tasking Environment.

In the FAP60 scenario, there were five true events that required revisions to a robot's route and four FAs that RoboLeader attempted to edit around when no events occurred. Participants could verify the validity of the RoboLeader recommendations by reviewing the map. A true event was associated with an icon (a red square for a Hostile Area and a blue square for a High Priority Area, see Figure 16-3), but FAs were not. In the FAP90 scenario, there were five true events that required revisions to a robot's route, and one FA. In the MP60 scenario, ten true events occurred that required revisions to a robot's route, though RoboLeader only provided solutions for two of them. In the MP90 scenario, ten true events occurred and RoboLeader provided solutions for eight of them.

In addition to the tasks described above, the participants simultaneously performed a gauge monitoring task and an auditory communications task. The gauge monitoring task (upper left corner of the OCU) displayed four gauges constantly in motion that entered an upper or lower limit at various pre-specified times throughout the scenarios. The participants were required to monitor the gauges and press a "Reset" button when any gauge entered the upper or lower limit to put the gauges back to their normal levels. The auditory communications task

presented pre-recorded questions at 30 sec intervals during the scenarios. The questions included simple military-related reasoning and memory tests. Participants used a keyboard to enter their responses for the questions into the communications panel on the OCU (adjacent to the gauges, see Figure 16-3).

Dependent measures included the number of targets located and identified, the number of routes successfully edited, the operators' SA of the mission environment, their concurrent task performance (gauge monitoring and auditory communications) and their perceived workload. A mixed design ANCOVA with Unreliability Type (FAP vs. MP) and Reliability Level (60% [Low] vs. 90% [High]) as the between-subject factors and Visual Density (High vs. Low) as the within-subject factor is used to evaluate the operators' performance differences among the four conditions. Participants' spatial ability (composite score of two spatial tests) and their attentional control survey scores were used as covariates.

Results showed that the type of RoboLeader unreliability (FAP vs. MP) affected operator's performance of visual scanning tasks (target detection, route editing, and situation awareness). There was a consistent effect of visual density for multiple performance measures. Participants with higher spatial ability performed better on the two tasks that required the most visual scanning (i.e., target detection and route editing). Participants' self-assessed attentional control was found to impact their overall multi-tasking performance, especially during their execution of secondary tasks (communication and gauge monitoring). The most important finding was the target identification superiority for the FAP condition compared to the MP condition. This was most likely caused by the visual accessibility of the route map making FA verification relatively easy, whereas the lack of alerts in the MP condition required participants to scan the map constantly thus missing the targets on the live video. This was reinforced by the finding that MP conditions resulted in better overall SA which is consistent with increased scanning.

16.8.3 Experiment 3

In 2010, the capabilities of RoboLeader were expanded to deal more specifically with dynamic re-tasking requirements for persistent surveillance of a simulated urban environment based on various battlefield developments as well as coordination between Unmanned Aerial Systems (UASs) and Unmanned Ground Vehicles (UGVs) in pursuit of moving targets in urban environments (Figure 16-4). In Experiment 3, we manipulated the level of autonomy of RoboLeader and examined its effect on the operator's performance (i.e., plan revisions for the robots, the concurrent target detection task, and SA of the mission environment) and workload [33]. The four levels of manipulation were as follows: Manual (no RoboLeader), Semi-Autonomous without Visualization, Semi-Autonomous with Visualization, and Fully Automated. The Semi-Autonomous condition was divided into two conditions so that the effect of the visualization tool could be evaluated. The visualization tool informed the participant of the synchronization of the robots as well as overall entrapment effectiveness of the target based on the movement of the target.

Figure 16-4: RoboLeader User Interface in Experiment 3.

During the scenarios, participants used their four robotic assets to pursue a primary moving target (a truck traveling at about 3 MPH) while monitoring the streaming video from the robots in order to find additional (secondary) targets (insurgents carrying weapons) in the mission environment. When the scenario for the Manual condition started, the participants entered waypoints for each UGV manually and adjusted the waypoints based on the movement of the primary target. In the Semi-Autonomous conditions, the participant selected an end point/location for the UGV at which time RoboLeader provided an optimum solution for reaching the desired destination. In the visualization condition, the user could consult the bar graphs as an indicator of whether their point selections were effective in terms of synchronization of the robots and entrapment of the target or if the plans needed revisions. The scores displayed in the visualization area were calculated based on the RoboLeader's encapsulation algorithm. Without visualization, the participant had to determine if they were properly cornering the target for capture. In the Fully Automated condition, RoboLeader provided the recommended end points as well as intermediate waypoints for each robot. The participant could accept, modify, or reject the plans. In each scenario, there were hostile areas (indicated by red squares on the map) that the robots needed to avoid. The order of experimental conditions was counterbalanced across participants.

The study was a within-subject design with RoboLeader's level of autonomy as the independent variable (with four levels: Manual, Semi-Autonomous without Visualization, Semi-Autonomous with Visualization, and Fully Automated). Dependent measures included the participants' performance of encapsulating the primary target (the encapsulation scores), the percentage of secondary targets (insurgents) detected, the participants' SA of the mission environment (percentage of SA queries answered correctly), and the participants' perceived workload. A repeated-measure analysis of variance with RoboLeader as the within-subject factor was used to evaluate the operator performance differences among the four conditions.

Results showed that RoboLeader (Fully Automated condition) was more effective in encapsulating the moving targets than were the human operators (when they were either without assistance from RoboLeader or when they were partially assisted by RoboLeader). Participants successfully encapsulated the moving targets only 63% of the time in the Manual condition but 89% of the time when they were assisted by RoboLeader. Those participants who played video games frequently demonstrated significantly better encapsulation performance than did infrequent gamers; they also had better SA of the mission environment. Visualization had little effect on participants' performance. Finally, participants reported significantly higher workload when they were in the Manual condition than when they were assisted by RoboLeader.

The difficulty levels of the tasks in the current study were fairly moderate. Instead of comparing the 4-robot and 8-robot conditions, the study could have investigated the effect of task difficulty. Different outcomes could have been observed in terms of the effectiveness and usefulness of RoboLeader.

16.9 LESSONS LEARNED

The lessons learned were many. Specifically for agents with less than perfect reliability having an easily verifiable display space mitigated problems with false alarms but not misses for the primary task of target identification. Most interesting was the superiority of experienced gamers for overall situation awareness. Future experiments will investigate mitigating factors for situation awareness well as target identification.

16.10 STUDY CONSTRAINTS/LIMITATIONS

The experiment was conducted in a virtual environment, not with actual robotic vehicles.

16.11 CONCLUSIONS

We concluded that future battlefields will be rife with manned and unmanned vehicles that will overwhelm the Soldiers' ability to conduct their assigned missions effectively unless technologies are developed to alleviate their multi-tasking requirements. This is particularly important because logistic efficiency will require Soldiers to conduct their missions in a many-to-one configuration. The purpose of the RoboLeader simulations was to understand how to develop a synergistic relationship between human supervisors having final decision authority and intelligent agents who supplies algorithmic solutions for many-to-one control problems. The initial experiment established the feasibility of using RoboLeader to control up to eight robots during a reconnaissance mission. The second experiment focused on RoboLeader's reliability level and type of possible errors. Surprisingly, operators were able to intervene more successfully with False Alarm Prone (FAP) error rates than with Miss Prone (MP) error rates contrary to previous findings in the literature. The apparent reason for this was that the more compact interface used in the current experiment allowed FAP verification to be accomplished more efficiently. In contrast, MP errors required operators to constantly scan the map reducing their target detection scores on the video displays. The final experiment showed the efficacy of RoboLeader in aiding the operator conduct more complex missions which required four robots to entrap a moving target.

16.12 FUTURE RESEARCH NEEDS AND PLANS IN THIS AREA

The capabilities of RoboLeader are currently being expanded to deal more specifically with dynamic re-tasking requirements based on battlefield developments (e.g., individual robots need to be re-tasked to search for a high-stake target) for persistent surveillance in urban environments.

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