RoboLeader

An Agent for Supervisory Control of Multiple Robots

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***Abstract*—We developed an intelligent agent, RoboLeader, that could assist human operators in route planning for a team of ground robots. We compared the operators' target detection performance in the 4-robot and 8-robot conditions. Results showed that the participants detected significantly less targets and had significantly worse situation awareness 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.**

Keywords- supervisory control; military; intelligent agent; individual differences; simulation

I. INTRODUCTION

Research showed that autonomous cooperation between robots can aid the performance of the human operators [1] and enhance the overall human-robot team performance [2]. Wang et al. [1] suggest that automating navigation-related tasks (e.g., path-planning) is more important than "efforts to improve automation for target recognition and cueing" (p.146) in the context of controlling a large team of robots. In the current study, we investigated whether RoboLeader, an intelligent agent that could interpret the operator's intent and issue detailed command signals to a team of robots of lower capabilities, could enhance the overall human-robot teaming performance [3]. The effects of individual differences factors (i.e., operator spatial ability [SpA] and attentional control) on operator performance were also evaluated [4]-[7].

II. METHOD

A. Partcipants

Thirty individuals (17 males and 13 females, mean age 24.73 years) from the Orlando, FL area participated in the study. They were compensated $15/hr for their time.

B. Apparatus & Procedure

1) Simulator and RoboLeader algorithm: The Mixed Initiative Experimental (MIX) Testbed was modified and used as the simulator. The Operator Control Unit (OCU) of the MIX testbed was modeled after the Tactical Control Unit developed under the ARL Robotics Collaborative Technology Allicance (Fig. 1). RoboLeader's path generator was designed for maximum search efficiency, and in utilizing simple concepts from vector mechanics, a unique behavior was given to the planning characteristics of the path generator which stands out from typical matrix search algorithms. Using vector mechanics, the path generator can be given a start point and an endpoint to navigate towards and the algorithm will "home in" on the intended destination. The path generator has the ability to wrap around the destination until an entry path is found.

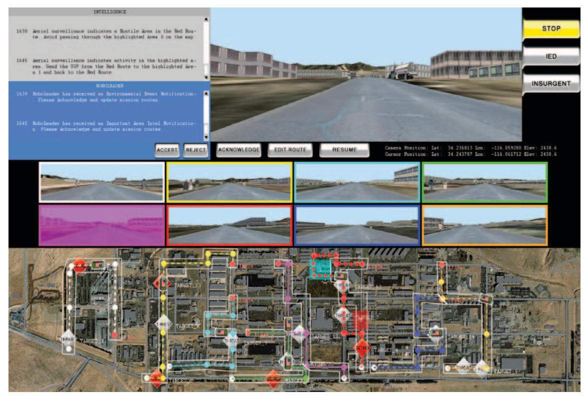

Figure 1. RoboLeader user interface.

2) Procedure: Participants were randomly assigned to the RoboLeader group or the Baseline (no RoboLeader) group. Participants first completed the pre-experiment surveys/tests (Attentional Control survey [4] and spatial tests [5][6]) and then received training, which lasted about 1 hr and consisted of PowerPoint® slides and practice tasks. Each experimental session had two scenarios, each lasting appr. 30 min, 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 robots in the other scenario. The order of scenarios was counter-balanced across participants. 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 must 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 route. Once an event transpired, the baseline participants had to notice that the event had occurred (via an auditory alert) and then re-route the robot that was affected by the event. In the RoboLeader condition, the RoboLeader would recommend plan revisions to the operator, who could either accept the plans or modify them as necessary. Out of these six events, three were “bottom-up” (e.g., unanticipated obstacles detected by the robots that obstructed their navigation) and three “top-down” (e.g., intel that the operator received from the intel network). In each scenario, there were five situation awareness (SA) queries (e.g., which of your robots is the closest to [Area of Interest]). 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. Participants assessed their workload (NASA-TLX) [8] after each scenario. The experimental session lasted about 1 hr.

A mixed-design ANCOVA 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’ SpA (composite score of the two spatial tests) and their attentional control survey scores were used as covariates. Dependent measures include number of targets located and identified, participants’ SA of the mission environment, as well as their perceived workload.

III. RESULTS

The data of insurgent and IED detection were merged to form the target detection data. The analysis showed that the participants detected significantly less targets when there were 8 robots compared to the 4-robot condition, $F(1,25) = 23.8$, $p < 0.0001$, indicating *less* efficiency with *more* resources/assets (Fig. 2). Those with higher SpA detected significantly more targets, $F(1,25) = 8.9$ ($p < 0.01$)(Fig. 2). These results are consistent with previous findings that individuals with higher SpA tend to exhibit more effective scanning performance and, therefore, are able to detect more targets than do those with lower SpA [7]. It is likely that the utility of RoboLeader was not sufficient to overcome the effect of SpA. In other words, the participants with higher SpA were able to outperform those with lower SpA, regardless of the RoboLeader condition. When there were 8 robots, the participants’ SA was significantly worse than when there were 4 robots, $F(1,26) = 13.3$, $p < 0.005$. Finally, participants experienced significantly higher workload when there were 8 robots compared to the 4-robot condition, $F(1,26) = 4.9$, $p < 0.05$ (Fig. 3), and those with poorer attentional control reported higher workload than did those with better attentional control, $F(1,26) = 7.2$, $p < 0.05$. Females also reported significantly higher workload (especially on the “Frustration” subscale) than did males, $F(1,28) = 12.2$, $p < 0.005$ (Fig. 3). Those participants in the RoboLeader group rated their workload as slightly lower than did those in the Baseline group, although the difference was not significant. Overall, it appears that the utility of RoboLeader was not fully actualized in the current study, possibly due to the simplistic nature of the path-planning task, although RoboLeader did save the participants approximately 3 min per mission (which lasted 20+ min), indicating enhanced efficiency with RoboLeader. In the follow-on study, we will investigate coordination between RoboLeader and heterogeneous air and ground robotic platforms in pursuit of moving targets in urban environments. Dynamic retasking (based on battlefield developments) will also be investigated.

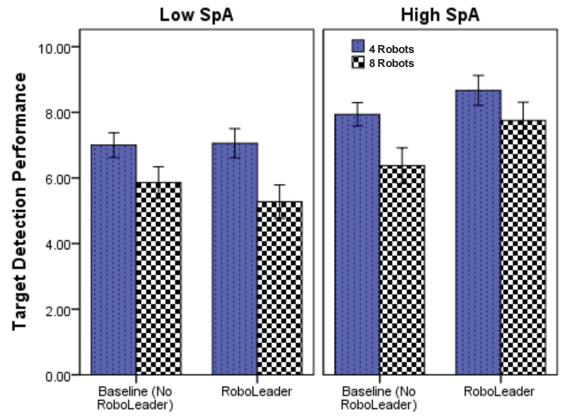

Figure 2. Target detection performance – insurgents and IEDs.

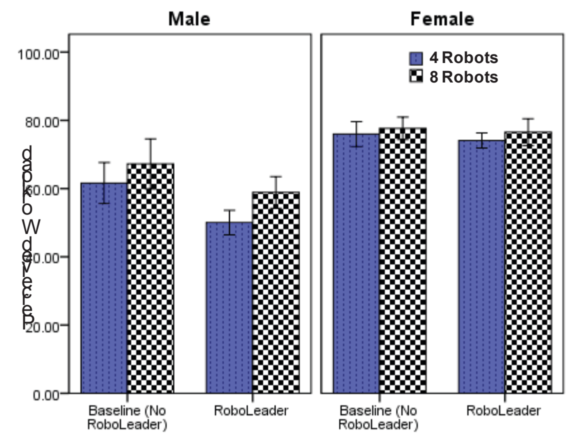

Figure 3. Perceived workload.

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