Influence of Situation Awareness on Control Allocation for Remote Robots

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***Abstract*—When remote robots operate in unstructured environments, they are typically controlled or monitored by an operator, depending upon the available autonomy levels and the current level of reliability for the available autonomy. When multiple autonomy modes are available, the operator must determine a control allocation strategy. We conducted two sets of experiments designed to investigate how situation awareness and automation reliability affected the control strategies of the experiment participants. Poor situation awareness was found to increase the use of autonomy; however, task performance decreased even when the automation was functioning reliably, demonstrating the need to design robot interfaces that provide good situation awareness.**

I. Introduction

At this time, the bulk of nontrivial robot application domains in non-structured environments involve remote robot operation using direct teleoperation or semi-autonomous robot control. There are many reasons for the low use of autonomy. While autonomy can be utilized when the task is well defined and the system operates in a structured environment, current robot technologies do not approach the same level of capability and reliability for less defined tasks and unstructured environments, making it difficult to deploy autonomous robots into these domains. In these situations, an operator must always be present, regardless of the level of autonomy present on the robot, typically referred to as human-in-the-loop control.

There are other implications for the use of autonomy in such domains. With an increased use of autonomy, operators switch to a more passive role of monitoring, a task that people have difficulty doing well. Such a passive role can cause loss of situation awareness. The side effect of this dynamic can influence control allocation when the automation reliability drops or when automation encounters a situation that it is not capable of handling. While the typical response of an operator under such circumstances should be to rely less on automation, poor situation awareness can force the operator towards a heavier reliance on automation. This poor control allocation strategy can have a detrimental effect on the overall performance.

Attaining high levels of situation awareness is difficult when remotely teleoperating a robot with noisy sensors in a dynamic and unknown environment over a delayed communication link with limited bandwidth. Researchers studying human-automation interaction have investigated the influence of automation reliability on control allocation; however, the interaction between situation awareness, automation reliability, and control allocation have not been thoroughly studied in human-automation research. Most experimental setups used are simulations of microworlds and do not adequately represent the complexities of operating a robot in the real world. The problem has not yet been studied in the human-robot interaction domain.

To determine the interaction between situation awareness, automation reliability, and control strategy for human-robot interaction, we conducted two sets of similar experiments. In the second set of experiments, the situation awareness of the participants was lowered by altering the user interface used to control the robot. Our hypothesis was that participants would rely more on automation in the low situation awareness experiments during periods of both high and low autonomy reliability. We also hypothesized that the participants would experience a higher workload in the low situation awareness experiment. Ultimately, the data presented below highlights the importance of designing user interfaces that foster better control allocation by improving an operator's situation awareness.

II. Prior Work

Parasuraman and Riley define automation as "the execution by a machine agent (usually a computer) of a function that was previously carried out by a human" [1]. Automation has traditionally been employed in systems that are complicated, tedious, or time critical, but it has also been used for economic reasons [1]. When automation was first introduced in the 1930's, its use was limited to large industries; however, at the present, automation can be found in many places, from home appliances to nuclear power plants.

Automation has always had weaknesses: in particular, it has only been effective in well-structured and controlled environments and continues to remain so. To avoid catastrophic failures in safety critical systems due to either flaws or limitations of automation, an operator must be present at all times to take control of the system. Situations of this kind in which a human operator is working with an automated system are referred to as "human-in-the-loop control." While a human operator may be beneficial in some situations, addressing the inadequacies of automation with human-in-the-loop control creates a different set of problems commonly referred to as out-of-the-loop problems [2]. These out-of-the-loop problems can be caused by a number of factors including loss of situation awareness [2]. When an operator is added to the system, improving the overall system performance requires more than simply optimizing operator performance and, separately, optimizing automation performance [3]. The interaction between the two needs to be considered as well.

For decades, researchers in the field of human-automation interaction have investigated the control allocation strategies of operators under different circumstances (ex: [4]–[6]) and observed how people use, misuse, or disuse automation (ex: [1], [7], [8]). Specifically, the influence of several factors including reliability on control allocation have been studied by several researchers; a detailed survey was conducted by Wickens and Xu [9].

While reliability is considered to be a significant influence on control allocation, there are other factors such as complacency, trust, workload, and user interface design that also influence the use of automation. For example, Wickens et al. [10] highlight the importance of user interfaces in automated systems and, according to Atoyan et al. [11], interface design plays an important role in influencing users' trust in automation. While user interfaces used in industrial and aviation automation are important, robot interfaces exert significant influence on remote robot operation [12], including a person's use, misuse or disuse of robot autonomy levels.

When teleoperating a remote robot, the operator is not co-located with the robot. The operator must rely on the user interface to attain adequate situation awareness to safely perform the task. The user interface is especially important in situations where the operating environment is dynamic and unknown. Burke et al. [13] determined that teleoperating a robot is common in application domains where robots operate in unstructured or high risk environments. Hence the user interface is especially important for these application domains.

Since Endsley [14] defined situation awareness, significant work has been done by researchers to examine the influence of situation awareness on performance in supervisory control systems (e.g., [15]–[17]). The interaction of situation awareness and workload with automation has also been highlighted by Parasuraman et al. [17]. There is also a need for attaining better situation awareness in human-robot interaction (e.g., [18], [19]).

Most of the research done has been in industrial or aviation automation and used low fidelity simulations, microworlds [20], or arbitrary tasks [20] in experimental setups. While the results from these experiments provide valuable insight, they lack the complexities of real world systems. The difference between using simulated systems and real world systems is more relevant while investigating human-robot interaction. For example, it can be difficult to convey the risks associated with remotely controlling a robot in simulation compared to controlling it in the real world. Though noisy sensors can be simulated, the uncertainties and dynamic nature of the real world cannot be adequately modeled.

To investigate the influence of low situation awareness on control allocation in a real robot system with variable reliability under high workloads we conducted two sets of similar experiments, varying the user interface slightly in the second set of experiments to reduce the operator's situation awareness.

III. METHODOLOGY

We conducted two sets of experiments, the first of which served as a baseline experiment to compare data against from the second experiment. The first experiment examined how operators' trust and control allocation strategy are impact by dynamic reliability and is therefore referred to as the 'Dynamic Reliability' (DR) experiment in this paper. The first experiment was conducted at two sites, University of Massachusetts Lowell (UML) and Carnegie Mellon University (CMU), and details of the experiment and analysis have been published by Desai et al. [21]. For the DR experiment, 12 participants were recruited at UML and CMU. The same code base was used for experiments at both sites, similar robots were used, and the course setup was similar as well. The data from both sites is therefore reported in aggregate.

For the second experiment (N=12), the situation awareness of the operators was reduced and hence is referred to as the 'Low Situation Awareness' (LSA) experiment. For both the DR and LSA experiments, participants experienced four different reliability profiles during their runs (autonomy working perfectly throughout the run (A), reliability dropping near the beginning of a run then increasing after a set period of time (B), reliability dropping in the middle of the run then increasing after the same period of time (C), and reliability dropping at the end of the run (D)). The participants for both experiments were approximately of the same age range [DR=27.2 (11.9), SA=28.08 (9.8), $t(26.5)=0.2$, $p=0.82$ (unpaired two-tailed t-test)].

For both DR and LSA, we used an iRobot ATRV-JR robot with a front mounted camera on a Directed Perception PTU-D46-17 pan-tilt unit and another camera mounted on the rear. For distance sensing, a SICK LMS200 was used on the front and a Hokuyo URG-04LX laser was mounted on the back. Participants could operate the robot in one of two autonomy modes, fully autonomous mode (FA) or robot assisted mode (RA), and were told that they could switch as often as they would like. In the RA mode, participants had a significant portion of the control and could easily override the robot's movements. The robot would provide its desired velocity vector based on the path it was supposed to follow. The robot's desired vectors were calculated the same way in both autonomy modes and were displayed on the user interface (UI) to show the participant the robot's desired direction. Participants used a gamepad to control the robot and interact with the UI.

Fig. 1 shows the UI used to control the robot. The video from the front camera was displayed in the middle, the video from the back camera was displayed on the top right (mirrored to simulate a rear view mirror in a car). The distance information from both lasers was displayed on the bottom around a graphic of the robot. The map of the course with the pose of the robot was displayed on the left. In LSA, three modifications to the UI were made. The pan-tilt

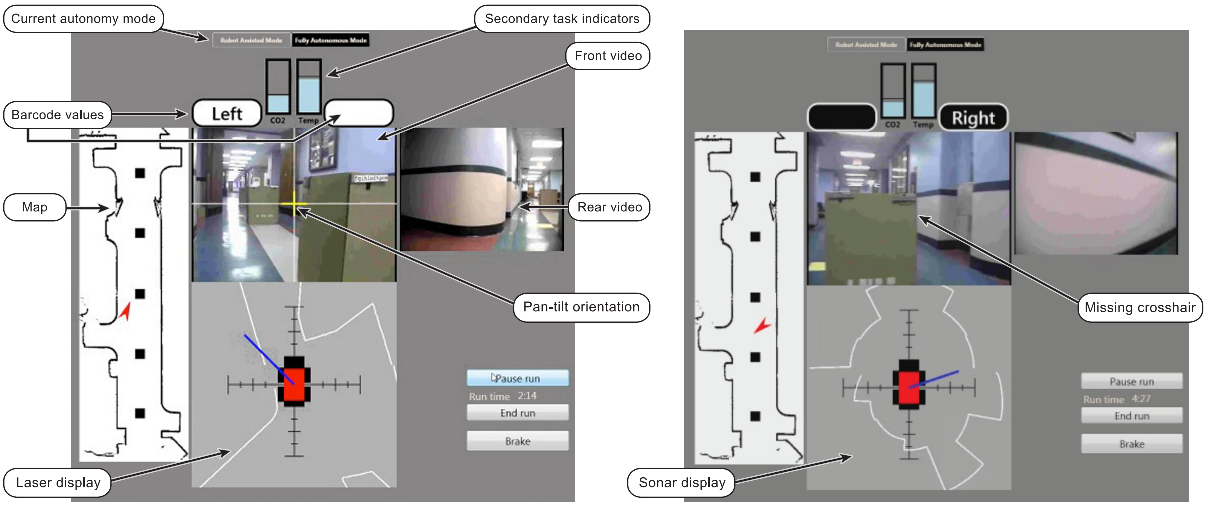

Fig. 1. The interface used in the DR experiments is shown on the left. The interface on the right, designed for the LSA, reduced the operator's situation awareness by removing the crosshairs indicating the orientation of the camera and by providing less accurate distance information around the robot.

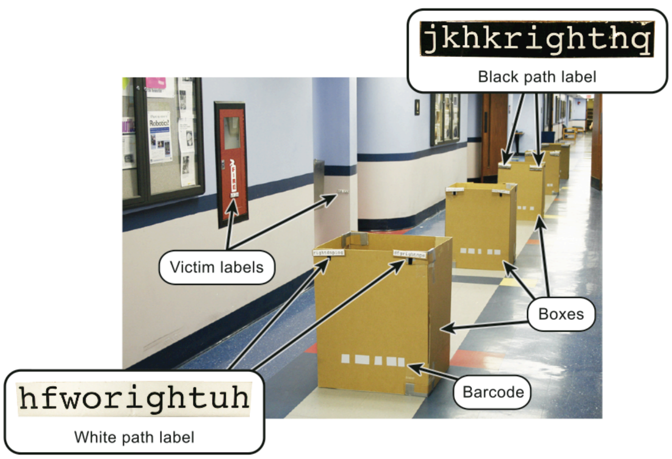

Fig. 2. The course used for the experiments. Boxes in the hallway had labels on them that indicated the path to be taken around the boxes.

indicators that were provided on the main video window in DR were removed in LSA. Second, the simulated sonar information replaced the more accurate laser range data provided in DR. Finally, the laser display in DR rotated in accordance with the pan value of the front camera, but this feature was disabled in the LSA interface and so the robot in the distance display always faced straight.

Participants were asked to drive the robot as quickly as they could along a specified path, searching for victims, not hitting objects in the course, and responding to the secondary tasks. To create additional workload, simulated sensors for CO_2 and temperature were used. Participants were asked to acknowledge high CO_2 and temperature values by pressing the corresponding buttons on the gamepad. The values were considered high when their values were above the threshold lines and colored red on the secondary task indicators.

Fig. 2 shows the course used, which was approximately 18 meters long, 2.4 meters wide, and had 5 obstacles (boxes) placed about 2.7 meters from each other. For each run, the participants were asked to follow a set path. We designed five different paths that had similar characteristics; analysis of experimental data shows that there were no significant differences.

Text labels were placed on top of the boxes to indicate the path ahead as shown in Fig. 2. The labels indicated 'left', 'right', or 'uturn'. The directions were padded with additional characters to prevent the participants from recognizing the label without reading them. Fig. 2 shows the two types of labels that were used. The labels with white background (referred to as white labels) were to be followed for the first half of the entire length and the labels with black background (referred to as black labels) for the second half. The transition from following the white labels to black labels was indicated to the participants via the UI.

The course also had four simulated victims. These victims were represented using text labels like the one shown in Fig. 2. The victim tags were placed on the walls of the course between 2.5 feet and 6 feet from the floor. The victim locations were paired with the paths and were never placed in the same location during the participant's five runs. Whenever the participants found a new victim, they were told to inform the experimenter that they had found a victim.

Using higher levels of automation reduces workload and hence is desirable, especially under heavy workload from other tasks. To prevent participants from using high levels of autonomy all the time, regardless of the autonomous system's performance, it is typical to introduce some amount of risk. Hence, in line with similar studies (e.g., [5], [22], [23]), the compensation was based in part on the overall performance. Participants could select a gift card to a local restaurant or Amazon.com. The maximum amount that participants could earn was \$30. Base compensation was \$10. Another \$10 was based on the average performance of 5 runs. The last \$10 was based on the average time needed to compete the 5 runs, provided that the performance on those runs was high enough.

After participants signed the informed consent form and filled out a pre-experiment demographic questionnaire, they were provided an overview of the robot system and the task to be performed. Then, participants were asked to drive the robot through the trial course in the FA mode. The experimenter guided the participant during this process, by explaining the controls and helping with tasks if necessary. The trial course was half the length of the test course. Once participants finished, they were asked to drive the robot again through the same course in the RA mode. Since there were multiple tasks that participants needed to perform, we decided to first show them the FA mode, as that would be a less overwhelming experience. Once the participants finished the second trial run, they were asked to fill out the post-run questionnaire, including subjective measurements of trust (Muir [24]), workload (NASA-TLX [25]), task performance (self, robot's), perceived risk of not receiving performance or time bonus payment. While the data from this questionnaire was not used, it allowed participants to familiarize themselves with it and also helped to reinforce some of the aspects of the run that they would need to remember.

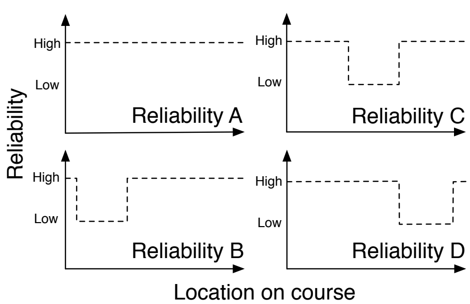

Fig. 3. Four reliability configurations were used during the experiments. In A, the autonomy worked the entire run. In B, C, and D, the autonomy reliability dipped, then recovered, at different times during the run.

After the two trial runs, the participants were asked to drive the robot for five more runs. In each run, a different map was used. During these runs the reliability of robot autonomy was either held high throughout the run or was changed. Fig. 3 shows the four different reliability configurations. The changes in reliability were triggered when the robot passed specific points in the course. These locations were equal in length and there were no overlaps. For all four patterns, the robot always started with high reliability. The length of each low reliability span was about one third the length of the entire course. Using different dynamic patterns for reliability allowed us to investigate how participants responded to a drop in reliability at different stages and the changes' influence on control allocation. Every participant started with a baseline run under full reliability (Reliability A in Fig. 3). Then, the four reliability profiles were counterbalanced for the remaining four runs.

Operator trust is known to influence control allocation [26], and research has shown that additional factors such as task complexity, reliability, and risk also influence trust [5]. To examine if change in situation awareness influences trust, we asked the participants to rate trust using the Muir's [24] scale.

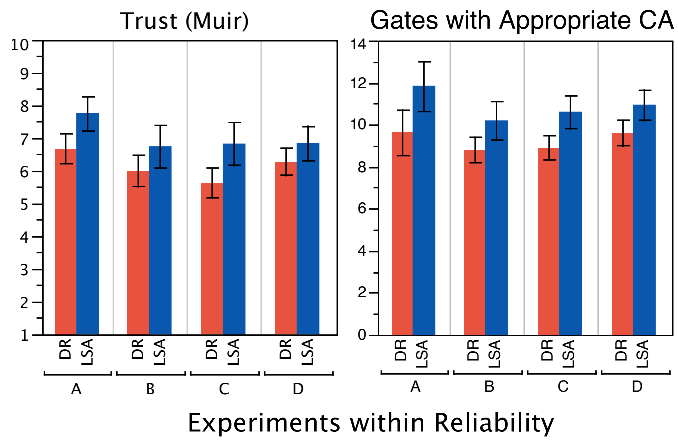

Fig. 4. Trust (left) and control allocation strategy (right) for DR and LSA experiments across reliability conditions, ± 1 std. error.

IV. Results and Findings

As planned, the altered user interface led to a noticeable difference in situation awareness. Participant responses to questions testing situation awareness showed better results for the DR experiment when compared to the LSA experiment, $t(96)$=-2.9 $p < 0.01$.

The objective performance and subjective data including operator trust were examined using a two-way ANOVA on the effects of Experiment (DR, LSA) and Reliability (A, B, C, D). Where appropriate a post hoc Tukey's HSD test was conducted to identify significant differences within effects. Of these, the highlights are listed in the following section.

A. Trust

A two-way ANOVA showed a significant effect for Experiment, F(1,139)=5.40, $p<0.05$. No significant effect was found for Reliability, F(3,139)=1.32, p=0.27 or the interaction, F(3,139)=0.14, p=0.93. Trust was significantly higher in LSA (μ=7.03, σ=2.02) than DR (μ=6.14, σ=2.22) (Fig. 4). This analysis shows that participants trusted the system more when their situation awareness was lowered. We suspect this might be due to the forced reliance on the fully autonomous mode.

B. Effect on Control Allocation

To examine how much the participants relied on the fully autonomous mode in both experiments we conducted a two-way ANOVA. The results of the analysis showed significant effects for Experiment, $F(1,135)$=4.22, $p<0.05$. No significant effect was found for Reliability, $F(3,135)$=2.37, p=0.07 or the interaction, $F(3,135)$=0.20, p=0.89. Participants relied significantly more on the fully autonomous (FA) mode in LSA (μ=9.74, σ=3.37) than in DR (μ=8.20, σ=4.74). This data indicates that participants did rely more on the autonomous behavior when their situation awareness was lowered.

We also wanted to examine if there was an increase in the autonomy mode switches due to lower SA. A two-way ANOVA for autonomy mode switches showed a significant effect for Reliability, $F(3,136)$=7.39, $p<0.01$. No significant effect was found for Experiment, $F(1,136)$=2.78, p=0.09 or the interaction, $F(3,136)$=1.51, p=0.21. A post hoc Tukey's HSD test showed that there were significantly fewer autonomy mode switches in Reliability A (μ=2.47, σ=3.39) compared to Reliability B (μ=6.05, σ=6.27, p<0.01) and Reliability C (μ=7.50, σ=6.13, p<0.01). While the difference between DR and LSA was only marginally significant, it did show that participants in LSA had more mode switches. This data indicates that, since the participants were forced to rely more on the FA mode, they might have been more cautious of the robot's actions and hence switched modes when appropriate and that led to a better control allocation strategy. Control allocation strategy is a metric that compares the operator's control allocation strategy with the ideal strategy [27].

To examine the control allocation strategy we conducted a two-way ANOVA. The results of the analysis showed a significant effect for Experiment, $F(1,135)$=7.08, p<0.01. No significant effect was found for Reliability, $F(3,135)$=0.78, p=0.50 or the interaction, $F(3,135)$=0.10, p=0.95. Control allocation strategy was significantly better in LSA (μ=10.85, σ=3.07) than DR (μ=9.21, σ=3.60) (Fig. 4) indicating that participants in LSA made better (more appropriate) use of the autonomous modes.

C. Performance

We analyzed the performance by looking at three metrics; the number of hits, the time taken to finish the task, and the number of wrong turns.

1) Hits: A two-way ANOVA for hits showed no significant effects for Reliability, $F(3,136)$=1.37, p=0.25, Experiment, $F(1,136)$=0.22, p=0.63, or the interaction, $F(3,136)$=0.66, p=0.57. This data shows that a drop in SA did not result in an increase in hits as expected. We suspect this was the case because of higher reliance on FA mode by participants in LSA, during which there were no hits.

2) Time: A two-way ANOVA for run time showed significant effects for Reliability, $F(3,136)$=6.37, p>0.01, Experiment, $F(3,136)$=9.05, p>0.01, and the interaction, $F(3,136)$=3.45, p>0.01. Participants in LSA took significantly more time (μ=687, σ=153) than participants in DR (μ=626, σ=102). A post hoc Tukey's HSD test for Reliability showed that participants took less time in Reliability A (μ=593, σ=92) then Reliability B (μ=677, σ=151, p<0.01) and Reliability C (μ=678, σ=126, p<0.01). This data matches our expectation that participants would need more time to perform their task when SA drops.

3) Wrong Turns: A two-way ANOVA showed significant a effect for Reliability, $F(3,136)$=11.95, p>0.01. No significant effect was found for Experiment, $F(1,136)$=0.16, p=0.68 or the interaction, $F(3,136)$=0.03, p=0.99. A post hoc Tukey's HSD test showed that there were fewer wrong turns in Reliability A (μ=0.08, σ=0.28) than in Reliability B (μ=2.05, σ=1.67, p<0.01), Reliability C (μ=1.61, σ=1.55, p<0.01), and Reliability D (μ=1.86, σ=1.69, p<0.01). This data indicates that even though participants in LSA had a better control allocation strategy they did not show an improvement in the number of wrong turns. We suspect this because they had a higher number of wrong turns in the robot assisted (RA) mode due to the lowered SA and higher workload.

D. Subjective Ratings

To investigate the impact on workload (NASA-TLX [25]), we conducted a two-way ANOVA. The results showed significant effects for Reliability, $F(3,136)$=3.69, p>0.05 and Experiment, $F(1,136)$=8.09, p>0.01. No significant effect was observed for the interaction, $F(3,136)$=0.15, p=0.92. The workload was significantly higher for LSA (μ=10.85, σ=4.14) than DR (μ=8.85, σ=4.03). A post hoc Tukey's HSD test showed that the workload was significantly lower for Reliability A (μ=7.43, σ=3.98), than Reliability B (μ=10.13, σ=4.11, p<0.05), Reliability C (μ=10.44, σ=4.19, p<0.05), and Reliability D (μ=10.07, σ=3.78, p<0.05). This data shows that participants in LSA felt higher workloads due to lower SA and similarly, the workload was exacerbated when reliability dropped.

We also looked at how reducing SA impacted participants' subjective ratings of performance and risk. A two-way ANOVA for self-performance rating showed a significant effect for Reliability, $F(3,136)$=4.21, p>0.01. No significant effect was found for Experiment, $F(1,136)$=0.11, p=0.73 or the interaction, $F(3,136)$=0.20, p=0.89. A post hoc Tukey's HSD test showed that self-performance rating in Reliability A (μ=5.55, σ=1.44) was significantly higher than the rating in Reliability B (μ=4.19, σ=1.70, p<0.01) and marginally higher than Reliability C (μ=4.52, σ=1.42, p=0.06) and Reliability D (μ=4.63, σ=1.67, p=0.06). This data shows that reducing SA did not impact their self-performance rating, but they did blame themselves for poor performance when reliability dropped.

A two-way ANOVA for the robot's perceived performance rating showed a significant effect for Experiment, $F(1,136)$=6.02, p>0.05. No significant effect was found for Reliability, $F(3,136)$=0.56, p=0.63 or the interaction, $F(3,136)$=0.50, p=0.67. The robot's performance rating was significantly lower in LSA (μ=5.77, σ=1.22) compared to DR (μ=6.21, σ=0.90). This data indicates that participants could have blamed the robot for providing poor SA.

A two-way ANOVA for perceived risk showed no significant effects for Experiment, $F(1,136)$=1.59, p=0.20, Reliability, $F(3,136)$=2.57, p=0.05, or the interaction, $F(3,136)$=0.08, p=0.96. We report Reliability as not significant as the subsequent post hoc Tukey's HSD test comparing the four reliability conditions did not result in any significant findings.

V. Conclusions

As expected, the drop in SA led to more reliance on autonomy; however, it did not result in better performance. While the amount of time needed increased due to the lower SA, especially during the RA mode, there was no difference in hits or wrong turns. We suspect that since participants drove more in FA mode in LSA, the number of hits did not increase. Also, as expected there was an increase in the workload. We expected the workload to increase in LSA because the participants would have to work harder to maintain sufficient SA. We found an increase in trust and suspect that was due to the increased reliance on the FA mode. However, it is surprising to find that the robot's performance rating decreased in LSA. We suspect the participants blamed the robot for the poor SA provided via the user interface.

All of these findings demonstrate the importance of situation awareness for remote robot tasks, even when the robot has autonomous capabilities. In real world situations, it is very likely that autonomous systems will experience periods of reduced reliability. Providing operators with the means to build up the best situation awareness possible will improve their use of the robot system. Based on these finding we recommend the following guidelines that would benefit operator interaction with remote autonomous robots:

- *Reduced SA leads to higher reliance on autonomous behaviors.* Intentionally reducing SA to force operators to rely on autonomous behaviors is not recommended as a design strategy due to the other undesirable side effects. However, such influence does remain a possibility, but should only be exercised when absolutely necessary, since doing so can potentially impact safety and performance.
- *Suspend or defer non-critical tasks when SA is reduced.* Even with higher reliance on automation, the workload is expected to increase, so tasks that are not critical should be suspended or deferred to offset the increased workload and to prevent an overall detrimental impact on performance.
- *Switch functions unaffected by reduced SA to automation.* Functions not impacted by reduced SA can be switched over to automation in an attempt to reduce workload.
- *Educate operators about SA.* Operators associate robot performance with SA and therefore operators must be informed (during training or during the interaction) that low SA does not necessarily impact the robot's performance.

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