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Using mixed-initiative human-robot interaction to bound performance in a search task

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Abstract

Mobile robots are increasingly used in dangerous domains, because they can keep humans out of harm's way. Despite their advantages in hazardous environments, their general acceptance in other less dangerous domains has not been apparent and, even in dangerous environments, robots are often viewed as a "last-possible choice." In order to increase the utility and acceptance of robots in hazardous domains researchers at the Idaho National Laboratory have both developed and tested novel mixed-initiative solutions that support the human-robot interactions. In a recent "dirty-bomb" experiment, participants exhibited different search strategies making it difficult to determine any performance benefits. This paper presents a method for categorizing the search patterns and shows that the mixed-initiative solution decreased the time to complete the task and decreased the performance spread between participants independent of prior training and of individual strategies used to accomplish the task.

1. INTRODUCTION

Mobile robots are increasingly used in dangerous domains, because they can keep humans out of harm's way. Despite their advantages in hazardous environments, their applicability and general acceptance in other less dangerous domains has not been apparent and, even in dangerous environments, robots are received with a last-possible choice acceptance. In a recent panel discussion with Lt. Col. Boyd¹ about the utility of robots for hazardous search missions, he stated that they (soldiers and commanders) are willing to put-up with robots because it reduces the likelihood that someone will die, other than that, robots do not really help the mission, but actually require more soldiers and more time, to accomplish the task than if the robot was not used [15].

In a different domain, but on a related note, Murphy, Casper, and Burke [6, 7, 16] have done substantial work on how robots should be integrated into operational first response teams and used to respond to actual emergencies. In their studies they demonstrated similar results to the

observations of Boyd in that more people were required to use the robots than if the robot was not in use, and the robot was most useful because it could go places that a human could not physically go, or that were deemed unsafe for human occupancy.

One of the reasons for the shortcomings in the general utility of robots in these domains is that they are usually fully teleoperated systems. The problem with teleoperated systems is that they require continuous operator involvement, but often distract the operator from the actual task of searching the environment. The reason for the distraction is that there is minimal sensory information provided back to the operator (usually only video [21]). Moreover, the operator is responsible to manage all the navigational elements of the task instead of focusing solely on the search aspect of the task.

The question then, is how to reduce the effort required for the user to operate robots in these domains? While training and experience with the robots is certainly an option, it results in only one person improving in their ability to control the robot. If that person is unavailable or preoccupied and someone else steps in, then performance again is based on individual training and experience. A better solution would be to make the robot itself a more effective tool in the hands of more operators, by reducing dependence on individual training and experience while maintaining high levels of performance.

To accomplish the goal of making the robot a more effective tool, researchers at the Idaho National Laboratory (INL) have been working on the design and implementation of a mixed-initiative human-robot interaction scheme. Mixed-initiative control is a challenging solution that orchestrates the strengths of the operator with the strengths of the robot into a single system that simplifies the interaction while maintaining a high level of performance. While designing and building the right level of interaction is necessary it is certainly more important to verify that what has been built does work and can effectively be used by the required end users, hence experimental validation plays a key role in the development of these systems.

This paper proceeds by first discussing related previous work and then summarizing the original dirty-bomb experiment. A solution for classifying navigational strategies is next discussed along with results from the classification.

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The paper concludes with a discussion and directions for future work.

2. PREVIOUS WORK

There has been substantial work in the domain of human-robot interaction. In this section we will review some of the expert-user experiments and prior efforts in mixed-initiative control. We then discuss previous, related work performed at the INL.

A. Expert user experiments

In an experiment reported by Burke et al. team communication and situation awareness were analyzed in a 16-hour urban search and rescue disaster response drill with teleoperated robots [6]. Casper and Murphy also presented lessons learned and observations from the use of teleoperated robots in a real, un-staged rescue response to the attack on the World Trade Center in September 2001 [7]. Lundberg, Christensen, and Reinhold discussed observations, benefits, and limitations of using a teleoperated robot with an army company that specialized in urban operations [14]. These examples explore how currently available, teleoperated robots could be integrated into a particular domain and used by domain experts. In contrast, our efforts are focused on working with domain experts to engineer and validate a new form of human-robot interaction that will improve task and mission performance over existing robot solutions.

Yanco et al. presented work comparing interface design elements in a mock urban search and rescue task using eight urban search and rescue professionals [22]. This experiment compared the visualization of information from the robots, while our current work is based on combining and orchestrating the visualization of the information and the amount of initiative afforded the robot. Another experiment reported by Hill and Bodt used two soldiers to explore the use of scalable interfaces (tablet vs. screen) and operator span of control with unmanned ground vehicles performing autonomous mobility and reconnaissance, surveillance, and target acquisition [8]. By comparison, our effort is based on combining the display and the initiative of the robot and then evaluating different levels of interaction.

B. Mixed-Initiative efforts

There have been a number of efforts to create human-robot interactions that leverage the strengths of the user with the strengths of the operator. Sometimes mixed-initiative interactions are referred to as adjustable autonomy [1, 19], sliding autonomy [2], or shared control [8, 13, 20]. Of these categories, the solution presented by Crandall and Goodrich, where they created a shared-control algorithm that modified the user's navigational commands based on range sensing, is perhaps the most similar to our current approach in that the user specifies the general direction for the robot to travel, but the robot is given initiative over how the robot will actually move. Our current efforts increase the robot initiative through the use of path-planning, guarded motion, and obstacle

avoidance algorithms, while allowing the operator to specify the goal, or direction of travel.

Other efforts in mixed-initiative solutions include Kaupp and Makarenko where the robot queries the human operator when the robot decides the human's information is worthwhile [12]. Their work was evaluated in simulation with plans to extend to a physical system. Fong's "collaborative control" is another approach that queries the human as a robot resource [9]. Additionally, Hong et al. use hierarchical Bayesian networks to prompt a human for missing information and to clarify ambiguous statements [11].

C. Previous work at the INL

Researchers at the INL have been actively engaged in creating solutions that support human-robot interactions. Initially the research was referred to as mutual initiative, then mixed-initiative, followed by facilitated initiative, and now seamless autonomy. Despite the variance in naming conventions, our goal at the INL has been to develop mixed-initiative solutions that work with commercial platforms and actually improve the utility of robots in a variety of settings. An essential design principle that has been shown to improve the utility of robots is the notion of *seamless autonomy*. Seamless autonomy is based on reducing the complexity of the human-robot interaction by abstracting information from the robot into a simplified interface and by supporting various metaphors for tasking the robot (e.g. go there, or look here, grab that, etc). Our research efforts have been validated over numerous user studies including novices [3, 17] and domain experts [4, 5, 18].

One of our recent experiments involved domain experts searching an environment for radiation sources. This experiment was originally reported in [4], but new analysis methods have revealed significant results were unavailable previously. We next review the "dirty-bomb" experiment and discuss the new findings.

3. DIRTY BOMB EXPERIMENT

A. Purpose

The purpose of our "dirty-bomb" experiment was to evaluate efforts at the INL to simplify and improve human-robot interaction. We refer to the efforts as "seamless autonomy."

In the experiment, participants were asked to use an INL modified iRobot PackBot and an INL operator control interface to explore a building in search of two radiation sources. Upon localizing the sources the users were asked to record the information on a paper floor plan and return the robot to the start location. Each participant performed the experiment with three different interaction schemes that each had a unique combination of interface design and robot initiative.

The facility for the experiment was an abandoned building at the INL that had a main hallway with a few side rooms. The environment was mostly planar with large obstacles placed throughout the environment. The rooms were occupied by common office furniture and some mechanical

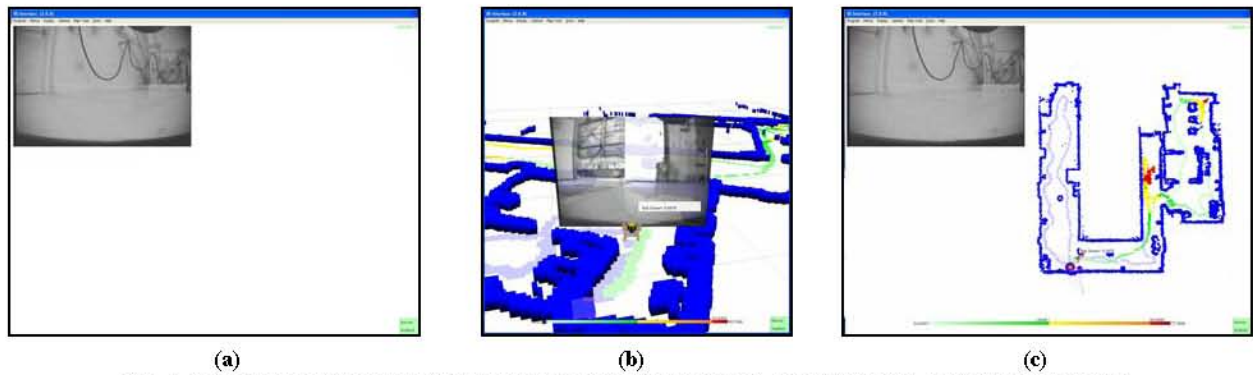


Fig. 1. Interface conditions used for the experiment: a) Joystick, b) Joystick + Map, and c) Target + Map.

equipment. Two radiation sources were hidden in the environment.

B. Conditions

Each operator drove the robot with each of three conditions. The first condition showed a live video feed from the robot and presented a radiation meter that looked and was used similar to real radiation meters, including the sounds regarding the relative radiation levels. In this condition, the operator controlled the robot via a joystick and the robot was given initiative to prevent collisions with obstacles by inhibiting movement towards detected obstacles. Figure 1a shows the interface for the “Joystick” condition.

The second condition was similar to the first except that the interface was augmented to include a robot constructed map of the environment along with abstractions representing the radiation readings as the robot moved through the environment. The operator viewed the robot and environment information from an egocentric perspective above and behind the robot. The operator controlled the robot via the joystick and the robot was given initiative to prevent collisions by inhibiting movement towards detected obstacles. Figure 1b shows the interface for the, “Joystick+Map” condition.

The third condition provided a third person perspective or bird’s eye view of the environment. The operator controlled the robot by moving a target icon with a mouse around the environment. Placement of the target in the environment indicates the operator’s goal for the robot and the robot is given the initiative to determine and follow a path to the destination point. Figure 1c shows the interface for the “Target” condition. The farther the target is moved from the robot, the more initiative is granted to the robot in terms of which internal behaviors are used. For instance, when the target is close, the robot does not perform path planning, whereas farther targets involve the robot planning a route.

C. Participants

Eighteen participants who could all be classified as domain experts were invited to participate in this study. The participants consisted of three groups based on prior training and experience. The first group of participants included seven Explosive Ordnance Disposal (EOD) personnel from the United States Army, Navy, and Air Force who all had more

than six months prior experience with in-field dirty-bomb response and in-theatre robot experience using iRobot’s PackBot. The second group included five Weapons of Mass Destruction Civil Support Team (CST) personnel and one combat engineer who all had prior experience with dirty-bomb response but no prior robot experience. The third group included five Nuclear Engineers (NE) who had prior experience with radiological hazards but no experience with radiological emergency response, dirty bombs, or robotics.

D. Initial Results

In the initial report on the experiment, results were discussed with respect to workload, subjective analysis, self-assessment questionnaires, collisions, frustration, mental demand, interaction time, and source localization accuracy, all of which suggested that the target condition was easier to use than other conditions of the experiment [4].

Despite these secondary observations that should have impacted the overall performance on the task, a substantial or significant difference in the time to perform the task, based on conditions, was not ascertainable from the recorded data, there was just too much variance. At the time of the first analysis we hypothesized that one of the reasons for the lack of a definitive improvement in the completion time is that participants in the experiment often demonstrated vastly different navigational strategies as they explored the environment. For example, some would move very meticulously, following each wall and curve of the environment, and others would move the robot right down the middle of the hallway. The variance in behavior was also somewhat evidenced by the variance in time to complete the task with some people finishing in as short as eight minutes and others taking as long as thirty minutes. The problem we had was that we did not have a way to systematically categorize the different navigational strategies.

4. DETERMINING NAVIGATIONAL STRATEGIES

When we perform experiments, we usually record all the information that is communicated between the operator and the robot and we use this data to understand how the operator actually used the robot, how often commands were sent and

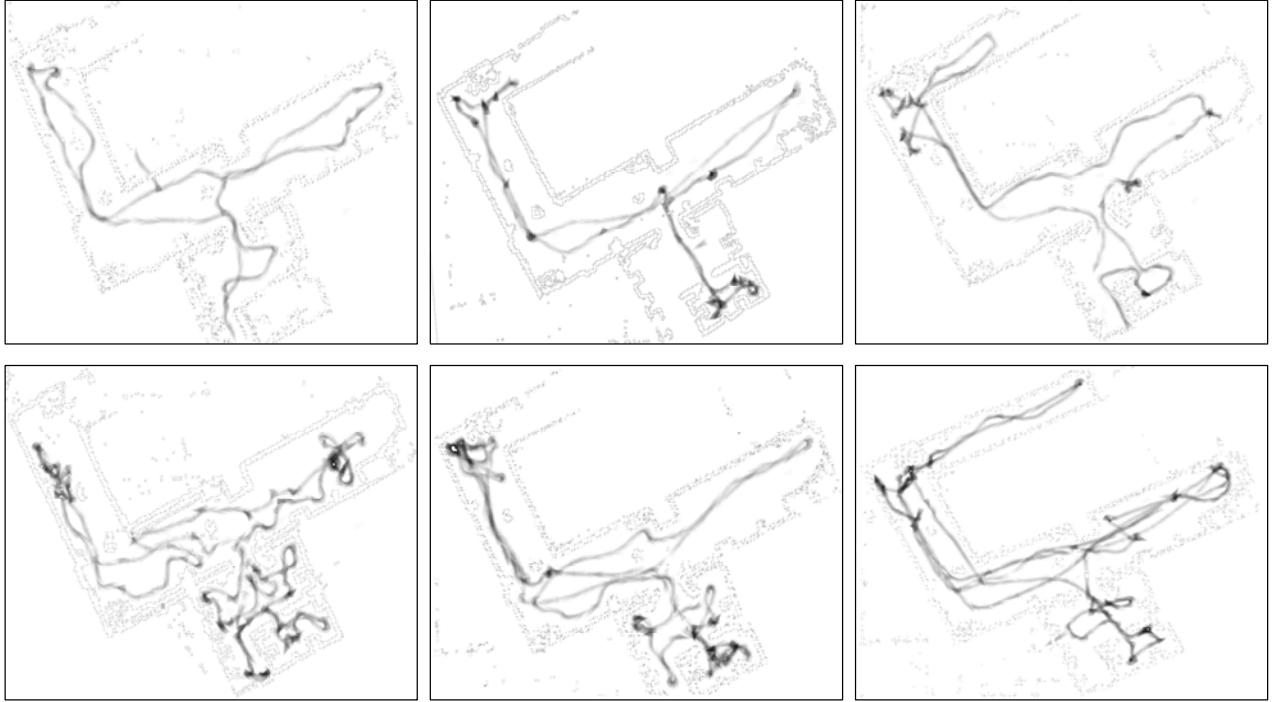


Fig. 2. Illustrations of the behavior classification. The top row illustrates swift behaviors and the bottom row illustrates meticulous behaviors. The two images on the left are the ones given as examples of the different behaviors. The four images on the right are examples of the images classified as similar to the corresponding image on the left.

what kind of information was returned from the robot. In this dirty-bomb experiment, the log of the communications was recorded and included time stamped information about the movement of the robot through the environment as well as information about the map built by the robot. This information allowed us to recreate the path taken by the robot as well as the environment mapped by the robot. In addition, to the pose information, the log file also provides a dwell time associated with each pose, which gives an indication of the relative speed by which the operator drove the robot through the environment.

A. Creating a Strategy Map

The obstacles in the robot-constructed map were retrieved from the log file and written to an image as an outline of the occupied area in the environment. The pose of the robot was rendered to the image as a light gray isosceles triangle pointing in the orientation of the robot as the robot moved. At each time increment, another light gray triangle was placed on the map to indicate the new pose of the robot. In this manner, the longer the robot persisted in once place, the darker the place became in the image. The result of this image manipulation is that the image now illustrates the route taken by the operator and how often the operator persisted at a single point, in essence, it created a map of the operator's navigational strategy. Example images are shown in Figure 2.

B. Classifying Strategies

The purpose of creating the strategy maps was to facilitate the classification of navigational behaviors. One observation of the original images was that each one had a different origin and map orientation because the original start coordinates and orientation of the robot were slightly different each time a new test was performed and a new map created. Because of this discrepancy in the look and feel of the maps, the images were aligned to the same coordinate space through an affine transformation matrix that was discovered based on a two point correlation between a base image and each additional image. This allowed each of the navigational strategies to be viewed in the same reference frame.

Once the strategy maps were adjusted to the same coordinate space, they were given to three researchers who were familiar with previous experiments at the INL. The participants were asked to classify the strategy based on the observed navigational patterns in each image. To provide a framework for comparison, the participants were given the two images on the left of Figure 2 and told that the image on the top represented one type of search behavior and the image on the bottom represented another type of search behavior. The participant was then asked to categorize each of the remaining images based on the similarity of the navigational strategy to that of one of the given images. Participants were asked to assign a '1' to the new image if the navigational strategy appeared more like the top left image and to assign a '9' to the new image if the navigational strategy appeared

more like the bottom left image. Participants were told to assign a ‘5’ if they could not decide between a ‘1’ or a ‘9’.

The classifications of the navigational strategy were then averaged between participants. If the average was less than four, then the strategy was classified as “swift”, if the average was greater than six, then the strategy was classified as “meticulous”, if the average was between four and six, the strategy was classified as undecided and not used for further analysis.

In total, there were 43 usable data sets to begin with. After this evaluation, 18 were classified as swift strategies and 20 were classified as meticulous strategies. Five of the data sets were classified as undecided and were removed from further analysis.

5. RESULTS

The purpose of sorting the images was to determine if there was any correlation between the navigational strategy used to search the environment and the time to complete the task. A secondary purpose was to determine, based on navigational strategy the effects on performance of using the mixed-initiative based “target” condition as compared to the other conditions.

When the data was organized according to navigational strategy and experimental condition, we observed that operators who used a more meticulous strategy took longer than those categorized with a swift approach, as would be expected. In the following discussion, significance was measured with a two-sample, unequal variance, two-tailed t-test.

In the Joystick Mode, operators who used a meticulous navigational strategy averaged 1305 ($\sigma = 287$) seconds while those who used a swift navigational strategy averaged 727 ($\sigma = 216$) seconds for a 44% improvement in time to complete ($p < .05$). With the Joystick + Map condition, operators who used a meticulous strategy averaged 975 ($\sigma = 251$) seconds while those who used a swift behavior averaged 698 ($\sigma = 85$) seconds ($p = .097$). With the Target + map condition, operators who used a meticulous strategy averaged 882 ($\sigma = 103$) seconds while those who used a swift behavior averaged 702 ($\sigma = 127$) seconds ($p = .061$). Figure 3 illustrates the relative time to complete the task between the different behaviors and navigational strategies.

Further analysis of the data reveals that in all three conditions, the operators completed the task in about the same time when they used the swift navigational strategy. The primary reason for this is that the maximum velocity of the vehicle was the same in each behavior, so whether the joystick was pressed all the way forward or the robot planned a path in the forward direction, the time to cover the distance would be about the same, and in our observations this was the case.

One of the interesting observations from this data is to directly compare the joystick mode with the target mode when using the meticulous search behavior. This comparison shows that there was a 32% decrease in time to complete the

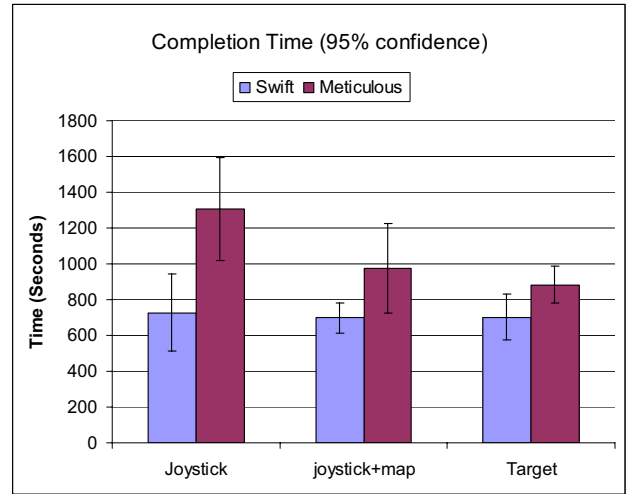


Fig. 3. Task completion times based on navigational strategy and experiment condition.

task using the target mode as compared to the joystick mode, even though the navigational strategy used to solve the task was considered the same.

What is interesting about this is that we know the results show no significant difference in the quality of the search or the ability to localize the sources between participants. We also know that a similar amount of the environment was searched with both the joystick and target conditions (based on the meticulous navigational strategy, so the reason for the decrease in time to complete the task was not based on searching less area. So, it must be based on taking less time to search the same area. However, we also know that the maximum speed of the robot for both the Joystick and the Target conditions was the same for both conditions. Therefore, we are left to conclude that when the joystick was used, the robot did not travel at its maximum velocity as often as when the target was used. If we consider that the robot, when planning a path to the target, would travel at its maximum velocity to get there, then every time the target or direction of the robot was moved, the robot would continue towards the target at maximum speed. By comparison, in joystick mode, the speed of the robot is set based on how far the operator presses the joystick. With all the twists and turn and changes in direction exhibited by the meticulous strategies, it is difficult for the operator to maintain the optimality with respect to the speed of the robot as it is moved through the environment.

6. CONCLUSION AND FUTURE WORK

The results and observations from this study suggest that when a well crafted human-robot interaction is used and the robot is given a useful level of initiative, then effect on the time to complete a task can be mitigated despite the operator’s choice of search strategy. As an example, consider the plot of the various times to complete the task for the Joystick vs. Target conditions shown in Figure 4. When

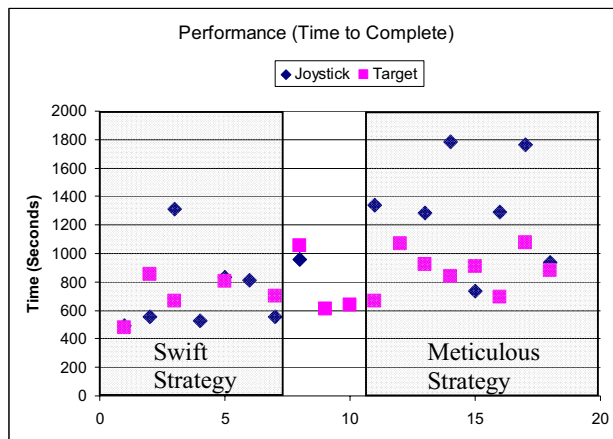


Fig. 4. Individual performance times for the different navigation strategies. The un-shaded region represents unclassified search strategies.

using the Joystick mode in the experiment, operators took between 8 and 30 minutes depending on their individual proficiency and the navigation strategy used. By comparison, the operators with the Target mode took between 8 and 18 minutes to finish the task, again depending on their individual proficiency and the navigation strategy they used. This means that the set of operators using target mode exhibited a 70% reduction in the performance spread between participants, or, independent of their individual proficiency and navigational strategy.

The notion of using the mixed-initiative target mode to mitigate effects on performance is further strengthened by the original findings that showed how the target mode mitigated the variance among individual performances with respect to the localization accuracy [4]. Together, the studies indicate that a properly constructed mixed-initiative solution mitigates performance variance that could be based on different levels of training and experience, or the type of strategy used to search the environment.

Based on this and previous studies, efforts are underway to design requirements and formalize procedures for using semi-autonomous robots in real-world hazard detection tasks with groups of end-users. Future development work is focused on identifying new and novel mixed-initiative approaches that can fundamentally improve the utility of mobile robots.

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