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Using Humans as Sensors in Robotic Search

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Abstract—**The human role in sophisticated information gathering systems is usually conceived to be that of the consumer. Human sensory and perceptual capabilities, however, outstrip our abilities to process information by a substantial amount. The use of human operators as "perceptual sensors" is standard practice for both UAVs and ground robotics where humans are called upon to "process" camera video to find targets and assist in navigation. In this paper we illustrate the human role as sensor referencing results of an earlier experiment investigating human performance of operator, navigator, or "perceptual sensor"tasks for teams of 4, 8, and 12 simulated pioneer P3AT robots. The experiment shows humans to be resource limited for the navigation/control task as the number of robots increases while the perceptual sensor function was less affected. We discuss the implications of using humans in a "perceptual sensor" role for information gathering from robotic teams and some of the difficulties including shifts in context and difficulties in developing situation awareness that are likely to arise.**

Keywords: **human-robot interaction, search and rescue, human roles.**

I. INTRODUCTION

Although humans are commonly viewed as the commanders, planners, and managers of complex human machine systems they could probably be better used playing less exalted roles. Humans are more noteworthy for their sensory feats (1010 audition/1013 vision dynamic range) than for immediate memory (3 bits) or controlled processing rates (3-4 bits/sec) [30]. Despite substantial advances in speech recognition, for example, human listeners are still needed when free speech must be extracted from a noisy environment. This pattern is repeated for cluttered visual environments where human operators are routinely used to review and identify targets in live video feeds and/or archival photographs or to pick faint signals off of radar, sonar, and other displays.

For mobile platforms, however, this perceptual strength has usually been treated as secondary to the task of navigating and driving robots and UAVs.

Section 2 presents Prior Research in scaling performance with numbers of robots. Section 3 introduces the USARSim simulation and section 4 describes the Experiment. Results are presented in section 5 and discussed in section 6.

A. Perception in Navigation

The near universal choice of camera-based control for situations with reliable, low latency communication suggests a commonly held belief that direct control is more efficient and less error prone than automated alternatives. When this implicit position is rarely discussed it is usually justified in terms of "naturalness" or "presence" afforded by control relying on teleoperation. Fong and Thorpe [8] observe that direct control while watching a video feed from vehicle mounted cameras remains the most common form of interaction. The ability to leverage experience with controls for traditionally piloted vehicles appears to heavily influence the appeal for this interaction style.

Control based on platform mounted cameras, however, is no panacea. Wickens and Hollands [30] identify 5 viewpoints that can be used for control. Three of them, immersed, tethered, and "plan view" can be associated with a moving platform while 3rd person (tethered) and plan views require external fixed cameras.

In the immersed or egocentric view the operator views the scene from a camera mounted on the platform. The field of view provided by the video feed is often much narrower than human vision, leading to the experience of viewing the world through a soda straw from a foot or so above the ground. This perceptual impairment leaves the operator prone to numerous, well-known operational errors, including disorientation, degradation of situation awareness, failure to recognize hazards, and simply overlooking relevant information [7,14]. A sloped surface, for example, gives the illusion of being flat when viewed from a camera mounted on a platform traversing that surface [10]. For fixed cameras, the operator's ability to survey a scene is limited by the mobility of the robot and his ability to retain viewed regions of the scene in memory as the robot is maneuvered to obtain adjacent views. A pan-tilt-zoom (ptz) camera resolves some of problems but introduces new ones involving discrepancies between the robots heading and the camera view, which can frequently lead to operational mishaps [32].

A tethered "camera" provides an oblique view of the scene showing both the platform and its 3D environment. The tethered view in which a camera "follows" an avatar (think Mario Brothers) is widely favored in virtual environments [15,19] for its ability to show the object being controlled in relation to its environment by showing both the platform and an approximation of the scene that might be viewed from a camera mounted on it. This can be simulated for robotic platforms by mounting a camera on a flexible pole, giving the operator a partial view of his platform in the environment [31]. However, the restriction in field of view and the necessity of pointing the camera downward limit this strategy's ability to survey a scene, although it can provide a view of the robot's periphery and nearby obstacles that could not be seen otherwise. The exocentric views show a 2 dimensional version of the scene such as might be provided by an overhead camera. It cannot be directly obtained from an onboard camera, but for robots equipped with laser range finders, generating a map and localizing the robot provides a method for approximating an exocentric view of the platform. In current experimental work in remotely controlled robots for urban search and rescue (USAR), robots are typically equipped with both a ptz video camera for viewing the environment and a laser range finder for building a map and localizing the robot. The video feed and map are usually presented in separate windows on the user interface and intended to be used in conjunction.

While Casper and Murphy [6] reporting on experiences in searching for victims at the World Trade Center observed that it was very difficult for an operator to handle both navigation and exploration from video information alone, Yanco and Drury [31] found that first responders using a robot to find victims in a mock environment made little use of the generated map. One possible explanation is that video is simply more attention grabbing than other presentations leading operators to control primarily from the camera while ignoring other available information.

A number of recent studies conducted by Goodrich, Neilsen, and colleagues [2,16,21,33] have attempted to remedy this through an ecological interface that fuses information by embedding the video display within the map. The resulting interface takes the 2D map and extrudes the identified surfaces to derive a 3D version resembling a world filled with cubicle partitions. The robot is located on this map, with the video window placed in front of it at the location being viewed. This strategy uses the egocentric camera view and the overhead view from the map to create a synthetic tethered view of the sort found most effective in virtual environments and games [15,23]. The anticipated advantages, however, have been difficult to demonstrate with ecological and conventional interfaces trading advantages across measures.

Of particular interest have been comparisons between control based exclusively on maps or videos. In complex environments with little opportunity for preview, maps, for example, have been found superior in assisting operators to escape from a maze [16]. When considering such potential advantages and disadvantages of viewpoints it is important, however, to realize that there are two, not one, important tasks that are likely to engage operators [23].

B. Navigation & Search

While the escape task favoring use of maps involved only navigation, the act of explicitly moving the robot to different locations in the environment, in many applications, search, the process of acquiring a specific viewpoint–or set of viewpoints–containing a particular object may be of greater concern. While both navigation and search require the robot to move, they differ in the focus of the movement. Navigation occurs with respect to the environment at large, while search references a specific object or point within that environment. Switching between these two subtasks may play a major role in undermining situation awareness in teleoperated environments. For example, since search activities move the robot with respect to an object, viewers may lose track of their global position within the environment, possibly requiring additional maneuvering to reorient the operator before navigation can be effectively resumed. Because search relies on moving a viewpoint through the environment to find and view target objects, it is an inherently egocentric task. This is not necessarily the case for navigation, which does not need to identify objects but only to avoid them. Search, particularly multi-robot search, presents the additional problem of assuring that traversed areas have been thoroughly searched for targets. This conflicts with the navigation task which requires the robot's camera to view the direction of travel in order to detect and avoid obstacles and steer toward its goal. If the operator attempts to compromise by choosing a path to traverse and then panning the camera to search as the robot moves, he runs both the risk of hitting objects while he is looking away and missing targets as he attends to navigation. For multirobot control these difficulties are accentuated by the need to switch attention among robots, multiplying the likelihood that a view containing a target will be missed. In earlier studies [28,29] we have demonstrated that success in search is directly related to the frequency with which the operator shifts attention between robots over a variety of conditions. An additional issue is the operator's confidence that an area has been effectively searched. In our natural environment we move and glance about, using planning and proprioception to knit the resulting views into a representation of our environment. In controlling a robot we are deprived of these natural bridging cues and have difficulty recognizing as we pan and tilt whether we are resampling old views or missing new ones. The extent of this effect was demonstrated by Pausch [18] who found that participants searching for an object in a virtual room using a headmounted display were twice as fast as when they used a simulated handheld camera. Since even the handheld camera provides many ecological cues we should expect viewing from a moving platform through a ptz camera to be substantially worse.

While navigation may impede search it may not be enough to simply move a user autonomously through an environment. Self-controlled users have demonstrated substantially better spatial knowledge than passive observers. Peruch [20], for example, determined that self-controlled viewers tended to develop a rich survey knowledge more quickly than passive observers. Self-controlled viewers not only remember what they see, but they also remember the actions they took to get there. Moreover, active viewers receive information on-demand. As such, the information they received was based on their particular needs, allowing them to examine a portion of the environment until it is understood. This suggests that active navigation might provide searchers with a better understanding of the environment outweighing the efforts devoted to active navigation.

To investigate the relation between human roles as a robot's controller or sensor we distinguish among three similar types of tasks: navigation, exploration, and foraging or search. In navigation [17,25] the operator has a complete map or aerial view and only needs to direct robots to their goals. In exploration [24] the operator begins without knowledge of the terrain which must be built up by a process of exploration. Foraging tasks [9,17] are a variant of exploration in which the operator searches for targets in the region being explored as well as guiding the robot. These three tasks place different demands on the operator with navigation requiring simple path planning, exploration requiring monitoring and reactive path planning, and foraging adding the requirement of searching for targets.

II. Prior Research

Previous studies [9,17,24] suggest that for foraging tasks using waypoint control the maximum N robots an operator can control lies somewhere between 4 and 9+ robots depending on the level of robot autonomy and environmental demands. Many of the tasks envisioned for robot teams, however, require larger numbers. To increase N robots we must increase robot autonomy, preferably in ways most compatible with operator capabilities. We hypothesize that the foraging task can be decomposed into exploration and perceptual search subtasks corresponding to navigation of an unknown space (controlling the robot) and searching for targets by inspecting and controlling onboard cameras (acting as a sensor). The reported study investigates the scaling of performance with number of robots for operators performing either the full task or only one of the subtasks to identify limiting factors. We presume that if a subtask is the limiting factor to increasing fulltask performance, performance on that subtask will parallel fulltask performance while the other subtask will exceed it

The logic of this comparison depends on the equivalence among the three conditions. In the fulltask condition operators used waypoint control to explore an office like environment. When victims were detected using the onboard cameras the robot was stopped and the operator marked the victim on the map and returned to exploration. Equating the exploration subtask was relatively straightforward. Operators were given the instruction to explore as large an area as possible with coverage judged by the extent of the laser rangefinder generated map. Because operators in the exploration condition did not need to pause to locate and mark victims the areas they explored should be strictly greater than in the fulltask condition. Developing an equivalent perceptual search condition is more complicated. The operator's task resembles that of the payload operator for a UAV or a passenger in a train, in that she has no control over the platform's trajectory but can only pan and tilt the cameras to find targets. The targets the operator has an opportunity to acquire, however, depend on the trajectories taken by the robots. If an autonomous path planner is used, robots will explore continuously covering a wider area than when operated by a human where pauses typically occur upon arrival at a waypoint. If human generated trajectories are taken from the fulltask condition, however, they will

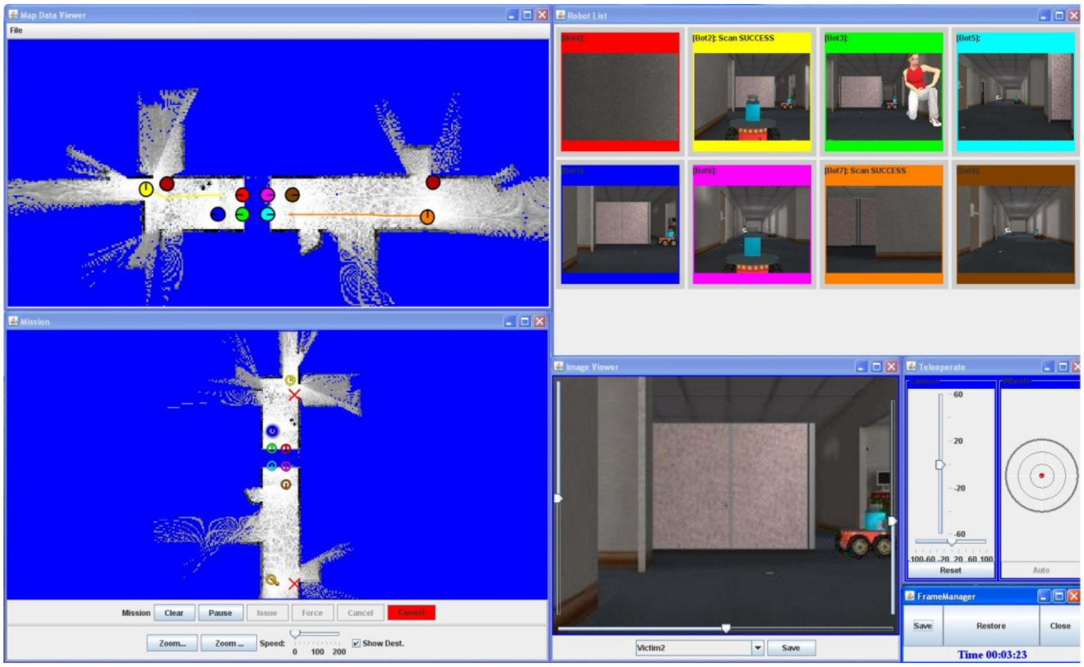

Figure 1 MrCS GUI

contain additional pauses at locations where victims were found and marked providing an undesired cue. Instead, we have chosen to use canonical trajectories produced by participants in the exploration condition since they should contain pauses associated withwaypoint arrival but not those associated with identifying and marking victims. A set of trajectories judged by the experimenters to be most typical in terms of areas covered and patterns of coverage were selected for each team size. As a final adjustment, operators in the perceptual search condition were allowed to pause their robots in order to identify and mark the victims they discovered.

III. III. USARSIM AND MRCS

The reported experiment [27] was performed using the USARSim robotic simulation with 4-12 simulated UGVs performing Urban Search and Rescue (USAR) foraging tasks. USARSim is a high-fidelity simulation of urban search and rescue (USAR) robots and environments developed as a research tool for the study of HRI and multi-robot coordination. USARSim supports HRI by accurately rendering user interface elements (particularly camera video), accurately representing robot automation and behavior, and accurately representing the remote environment that links the operator's awareness with the robot's behaviors. USARSim can be downloaded from www.sourceforge.net/projects/usarsim and serves as the basis for the Virtual Robots Competition of the RoboCup Rescue League. USARSim uses Epic Games' UnrealEngine2 [26] to provide a high fidelity simulator at low cost. Validation studies showing agreement for a variety of feature extraction techniques between USARSim images and camera video are reported in Carpin [3]. Other sensors including sonar and audio are also accurately modeled. Validation data showing close agreement in detection of walls and associated Hough transforms for a simulated Hokuyo laser range finder are described in [4]. The current UnrealEngine2 integrates MathEngine's Karma physics engine [13] to support high fidelity rigid body simulation. Validation studies showing close agreement in behavior between USARSim models and real robots being modeled are reported in [5,11,19,22,34].

MrCS (Multi-robot Control System), a multirobot communications and control infrastructure with accompanying user interface developed for experiments in multirobot control and RoboCup competition [23] was used in these experiments. MrCS provides facilities for starting and controlling robots in the simulation, displaying camera and laser output, and supporting inter-robot communication through Machinetta a distributed mutiagent system. Figure 1 shows the elements of the MrCS. The operator selects the robot to be controlled from the colored thumbnails at the top of the screen. To view more of the selected scene shown in the large video window the operator uses pan/tilt sliders to control the camera. Robots are tasked by assigning waypoints on a heading-up map on the Mission Panel (bottom right) or through a teleoperation widget (bottom left). The current locations and paths of the robots are shown on the Map Data Viewer (middle left).

IV. EXPERIMENT

A. Participants

45 paid participants, 15 in each of the three conditions, were recruited from the University of Pittsburgh community. None had prior experience with robot control although most were frequent computer users.

B. Procedure

After collecting demographic data the participant read standard instructions on how to control robots via MrCS. In the following 20 minute training session, participants in the fulltask and exploration conditions practiced control operations. Participants in the fulltask and perceptual search conditions were encouraged to find and mark at least one victim in the training environment under the guidance of the experimenter. Participants then began three testing sessions (15 minute each) in which they performed the search task using 4, 8, and finally 12 robots. After each task, the participants were asked to complete the NASA-TLX workload survey.

C. Experimental Conditions

A large USAR environment previously used in the 2006 RoboCup Rescue Virtual Robots competition [1] was selected for use in the experiment. The environment was a maze like hall with many rooms and obstacles, such as chairs, desks, cabinets, and bricks. Victims were evenly distributed within the environment. A second simpler environment was used for training. The experiment followed a between groups repeated measures design with number (4, 8, 12) of robots defining the repeated measure. Participants in the fulltask condition performed the complete USAR task. In the subtask conditions they performed variants of the USAR task requiring only exploration or perceptual search. Participants in the fulltask condition followed instructions to use the robots to explore the environment and locate and mark on the map any victims they discovered. The exploration condition differed only in instructions. These operators were instructed to explore as much of the environment as possible without any requirement to locate or mark victims. From examination of area coverage, pausing, and other characteristics of trajectories in the fulltask and exploration conditions a representative trajectory was selected from the exploration data for each size of team. In the perceptual search condition operators' retained control of the robots' cameras while robots followed the representative trajectory except when individually paused by the operator.

TABLE I

Full task	Search & exploration
Exploration	Discover & map new regions
Perceptual Search	Id targets in visual field

V. RESULTS

Data were analyzed using a repeated measures ANOVA comparing fulltask performance with that of the subtasks. Where measures were inappropriate for some subtask comparisons are pairwise rather than tripartite. Number of robots had a significant effect on every dependent measure collected (lowest N switches in focus, $F_{2,54} = 12.6$, $p < .0001$). The task/subtask conditions also had nearly universal effects. The N robots x task/subtask interaction that would indicate differential scaling in N robots was less robust but found for the most crucial performance measures. Overall fulltask participants were successful in searching the environment at all team sizes finding as many as 12 victims on a trial. The average number of victims found was 4.8 using 4 robots, 7.06 for 8 robots, but dropping back to 4.73 when using 12 robots. Participants in the perceptual search condition, however, were significantly more successful, $F_{1,28} = 27.4$, $p < .0001$, finding 6.93, 8.2, and 8.33 victims respectively. As shown in Figure 2 search performance in the perceptual search condition improved monotonically albeit shallowly while fulltask performance peaked at 8 robots then declined resulting in a significant N robot x Task interaction, $F_{2,56} = 8.45$, $p = .001$.

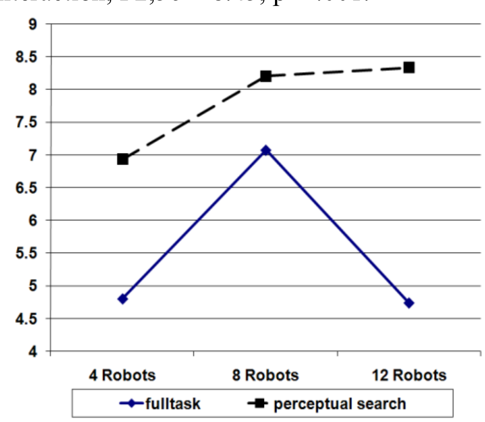

Figure 2. Victims Found as a function of N robots

As figure 3 shows, coverage for the fulltask and exploration conditions was nearly identical at 4 and 8 robots but diverged at 12 robots, (between groups $F_{1,27} = 11.43$, $p = .002$, fulltask x N robots $F_{2,54} = 4.15$, $p = .021$) with perceptual search participants continuing to improve while those in the fulltask condition declined.

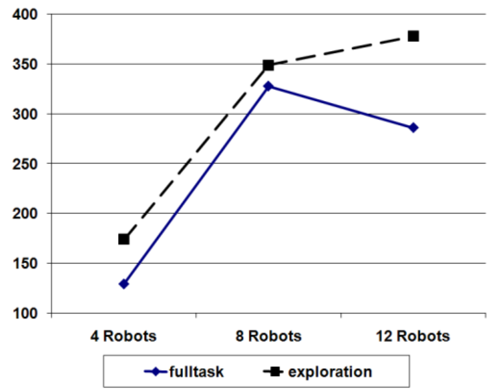

Figure 3. Area in sq meters Explored as a function of N robots

Of the process measures, switches in focus among robots most strongly differentiated among groups with perceptual search participants switching far less than those involved in exploration. Workload (Figure 4) increased monotonically in all groups but was substantially lower, $F_{1,27} = 21.17$, $p < .0001$, in the perceptual search condition.

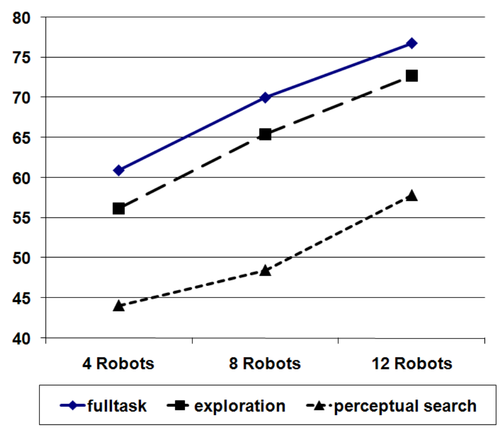

Figure 4. Workload as a function of N robots

Pause Times

Pause times were analyzed to examine the premises used to equate conditions for this experiment more closely. Task had a significant effect on every dependent measure collected. The number of robots controlled also had universal effects. For this analysis, pause times reported for perceptual search reflect only those pauses originated by participants in this condition and not pauses contained in the programmed trajectories. As shown in Figure 5, across robots and tasks a diverse range of pauses were observed with significantly more short pauses in the 0~20 sec range found for the fulltask and navigation conditions than in the perceptual search condition. We believe that pauses of this duration were most commonly associated with navigation and assigning new waypoints. At the opposite end, for time periods beyond 120 sec (10+% of session), we presume the robot to have been neglected, probably at a terminal waypoint rather than paused in performance of a task. We presume pauses in the medium range of 40~120 sec to reflect a mixture of pauses for navigation and victim identification and marking. The plausibility of this conjecture can be seen by superimposing pause times from the perceptual search condition on pause times from the other two conditions.

Adding perceptual search pause times to navigation pause times brings them closer to those of the fulltask condition supporting our contention that the navigation task is being performed in a similar fashion in the two conditions. Conversely, perceptual search pauses in this range are strictly fewer than in the fulltask condition supporting the interpretation of victim identification and marking as a contributor but not solely responsible for pauses in this range.

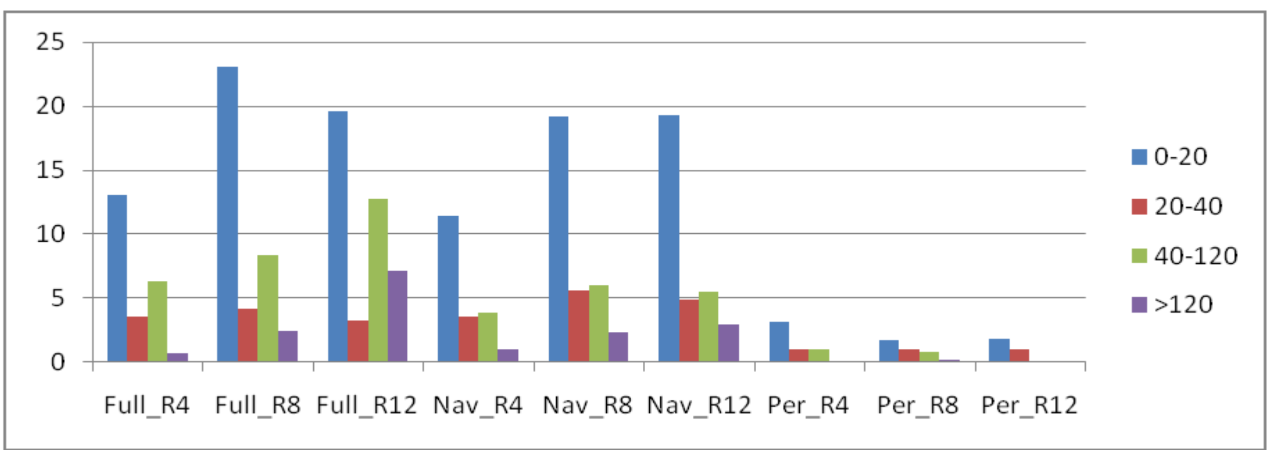

Figure 5. Pause durations in seconds

As figure 6 shows total pause duration for the fulltask and exploration conditions was nearly identical at 4 and 8 robots but diverged at 12 robots, (between groups $F_{1,29} = 12.11$, $p < .001$) with aggregate pauses in the fulltask condition greatly exceeding those in exploration. Pause duration per robot follows a similar pattern with the fulltask and exploration conditions being nearly identical at 4 and 8 robots but diverging at 12 robots, (between groups $F_{1,29} = 6.225$, $p = .0025$

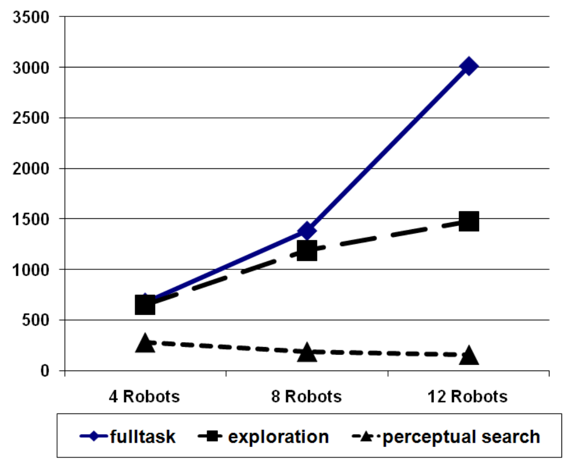

Figure 6. Aggregate pause duration

VI. Discussion

While Peruch [19] and others have argued that user control of a robot was needed to develop adequate situation awareness and survey knowledge to perform foraging tasks our data suggest active control may actually be detrimental for high workload tasks such as multirobot control and monitoring. Our data show that exploration performance as N robots was increased was very similar in the fulltask and exploration conditions indicating that the cognitive resources freed up by eliminating perceptual search in the exploration condition provided very little advantage to operators who were already devoting the lion's share of their efforts to exploration.

Victim finding performance in the perceptual search condition, by contrast, increased as robots were added. This improvement was, if anything, underestimated in our experiment due to a ceiling effect because of the relatively small size of the map and the number of victims available for rescue. This interpretation is borne out by the workload ratings which show perceptual search operators found themselves relatively unloaded even when monitoring video streams from 12 robots. Fulltask and exploration operators, by contrast, reported being heavily loaded even with 4 robots and approached the top of the scale when confronted with 12. Pause times and measures of neglect similarly show fulltask and exploration operators far more likely to neglect robots particularly as their number increases. For fulltask operators this led to a breakdown in performance at the twelve robot level where they were no longer able to adequately task their robot team (neglected robots) or perform perceptual search (found only half the victims as those not required to control exploration). For this situation, at least, a preferred task allocation would assign exploration which involves path planning, mapping, and minimal coordination to autonomous robots and assign the human the task of monitoring video and acting as a sensor.

In deployed systems such as Predator or Global Hawk multiple operators are separately assigned sensor and navigation tasks. With the increasing numbers of unmanned platforms mandated by congress future operators are likely to be responsible for multiple platforms. If these platforms must be coordinated as would be necessary to acquire multiple views of a target, for example, the complexity of control could be expected to grow exponentially [12] in the number of platforms rather than linearly as in our experiment. Our results suggest that under these conditions automating navigation and coordination of the platforms will be necessary and the most appropriate role the operator can serve is that of a sensor and information fuser. To be effective at this role, however, requires we develop approaches to shared control that allow the operator to guide the platforms in an observation rather than navigation oriented fashion. In the resulting human-machine system the operator would play a central role across the for levels of fusion from serving as an EO sensor to directing the system to acquire new information.

Acknowledgements

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