Towards Predicting Robot Team Performance *

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Abstract – *In this paper we develop a method for predicting the performance of human-robot teams consisting of a single user and multiple robots. To predict the performance of a team, we first measure the neglect tolerance and interface efficiency of the interaction schemes employed by the team. We then describe a method that shows how these measurements can be used to estimate the team's performance. We validate the performance prediction algorithm by comparing predictions to actual results when a user guides three robots in an exploration and goal-finding mission; comparisons are made for various system configurations.*

1 Introduction

In order to understand the workload and performance of a system, we have previously identified two concepts that help determine the usefulness of a system: how much the robot can do autonomously and how much the robot supports human interaction [2]. These concepts were previously captured in two metrics, namely, *neglect tolerance* and *interface efficiency*. Based on measurements of the neglect tolerance and interface efficiency of various interaction schemes, we can determine a random process that estimates the performance of a single-robot controlled by a given interaction scheme.

In order to predict the performance of a multi-robot team, we first measure the neglect tolerance and interface efficiency of two control schemes: *point-to-point* (P2P) and *region-of-interest* (ROI) in an exploration and goal-finding experiment. We then describe a method for combining the expected performance of individual interaction schemes to predict the performance of multi-robot systems. We use this performance prediction algorithm to predict the performance of a three-robot system where a user guides the robots via various combinations of the two interaction schemes. We then compare the predicted performances with the actual performances of teams consisting of a human and three robots.

2 Related Work

Arkin's group has done a lot of work in robot teaming. Such work includes the teleoperation of a group of robots by a single input from an operator [1]. This same idea was used in [6] for telemanipulation. Goldberg's work in [5] is related to this idea. However, instead of having one operator control multiple robots, Goldberg has many operators control one robot. This is important because it provides a foundation for multiple user/multiple robot interactions.

A powerful principle for human-robot systems is the principle of adjustable autonomy. The term adjustable autonomy captures the notion that the autonomy level of a robot can be changed. This principle has been used extensively in the literature (e.g., [4], [10]). An important principle related to adjustable autonomy is that of mixed-initiatives[11], which poses the question of who has control in a system at a given moment and who is responsible for initiating control transitions. Scerri and associates have developed methods which address the issues of adjustable autonomy and mixed-initiatives in [12].

In previous work, we have been testing various interaction schemes and monitoring the success of them for various experiments. In [8] we performed experiments with 10 individuals each controlling a team of three robots. We used teleoperation, point-to-point and region-of-interest interaction schemes each of which allow the robot different levels of automation. The results of the experiment show general trends which indicate that by decreasing the level of autonomy of the robot, the user can increase performance at the cost of increasing workload. We also have developed a method for determining values representing the actual performance and workload of various interaction schemes [3]. We found similar tradeoffs between the various interaction schemes. Furthermore, Olsen and Goodrich discuss important metrics for evaluating human-robot interactions [9]. With the intuition garnished from previous experiments about the nature of human-robot interactions, we now aim to predict the expected performance of multi-robot teams.

3 Neglect Tolerance and Interface Efficiency

The metrics of *neglect tolerance* and *interface efficiency* measure the performance of a robot given the frequency and duration of human-robot interactions. The metrics are described in greater detail in [2, 3], but we describe them briefly in this section.

3.1 World Complexity

It seems obvious that it would be easier for a robot to navigate through an uncluttered world as opposed to a cluttered world. Thus, both the neglect tolerance and interface efficiency metrics depend on estimates of world complexity. Estimating world complexity can be somewhat subjective, and a thorough treatment of it is beyond the scope of this paper. For a more detailed discussion of estimating world complexity, see [2].

3.2 Neglect Tolerance

Neglect tolerance is a measure of the effectiveness of a robot's autonomy mode. The term is used to refer to the way in which a robot's expected performance changes when it is neglected by humans; i.e., when human attention is focused elsewhere. As a general trend, when neglect increases robot performance decreases. The magnitude of the decrease in robot performance is dependent on the scheme used for interacting with the robot. Figure 1 conceptualizes how one might expect neglect to affect robot performance for various interaction schemes. In the figure, the performance of an interaction scheme using a teleoperated robot degrades quickly when the human neglects the robot. The performance of an autonomous robot does not tend to change when it is neglected, but the peak performance tends to be lower than that of a teleoperated robot. Furthermore, there are an assortment of interaction schemes between the extremes of teleoperation and full autonomy that have varying levels of neglect tolerance.

Let π be an interaction scheme, which is the combination of an interface and a robots artificial intelligence. The neglect tolerance of π is defined by the random process $V_N(\pi; t_{\text{off}}, c)$, where t_{off} is the time since the robot was neglected by the human and c is world complexity. For simplicity, we often denote $V_N(\pi; t_{\text{off}}, c)$ as $V_N(\pi)$.

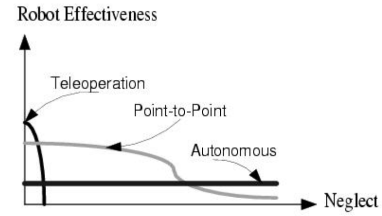

Figure 1: Qualitative representations of neglect tolernace for various interaction schemes.

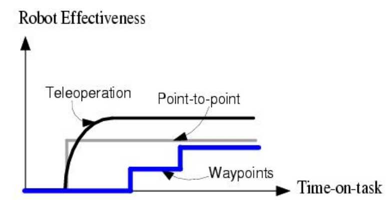

Figure 2: Qualitative representations of interface efficiency for various interaction schemes.

3.3 Interface Efficiency

Interface efficiency is a measure of the effectiveness of the interface between a robot and a human. When the attention of a human operator is turned back to a robot, we expect the performance of the robot to change, hopefully for the better. The way in which robot performance changes during interactions depends on the interaction scheme employed by the robot. The interface of an interaction scheme affects the time it takes for a human to gain sufficient situational awareness, decide on a course of action, determine the inputs to give the robot, and then communicate those inputs to the robot. Figure 2 shows how interface efficiency could hypothetically affect the performance of a robot for different interaction schemes. The figure expresses the idea that changes in an interaction scheme affect the way the performance of a robot changes during interactions.

The interface efficiency of an interaction scheme π is defined by the random process $V_S(\pi; t_{\text{on}}, c, t_N)$, where t_{on} is the time elapsed since the current human-robot interaction began, c is world complexity, and t_N is how long the robot was neglected prior to the current human-robot interaction. For simplicity, we denote $V_S(\pi; t_{\text{on}}, c, t_N)$ as $V_S(\pi)$.

3.4 Measurement Technology

The random processes $V_N(\pi)$ and $V_S(\pi)$ can be estimated nonparametrically via user studies. In the user studies, secondary task experiments are used to cause the user to turn attention from one task to another. This causes the robot to be neglected so that the domain space of the random processes can be sampled adequately. For a detailed description of the measurement technology, see [2, 3].

3.5 Combining neglect tolerance and interface efficiency

The performance of a semi autonomous robot declines as human attention is spent on other tasks and/or the complexity of the world increases. Additionally, effective human-robot interactions should allow performance levels to remain high. These imply that interactions between a human and a robot must be frequent enough and last long enough to maintain sufficiently high robot

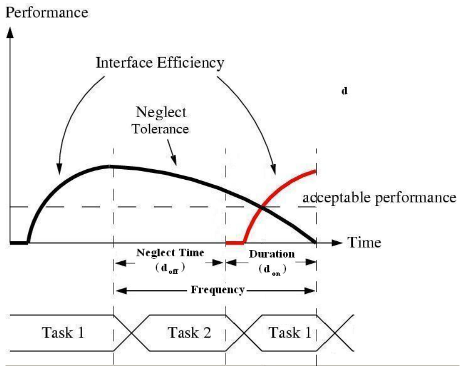

Figure 3: Measures of neglect tolerance and interface efficiency can be combined to obtain acceptable interaction rates, each of which corresponds to a different average robot performance.

performance levels. A combination of the neglect tolerance and the interface efficiency of an interaction scheme defines the frequency and duration of the interactions necessary to maintain a particular performance level.

To illustrate this, consider Figure 3. In the figure, moving from left to right along the horizontal axis, a robot begins at performance level zero. A human operator begins to interact with the robot (Task 1). When this occurs, performance is modeled as an interface efficiency curve (see Figure 2). When a human terminates the interaction and turns his/her attention elsewhere (Task 2), the robot performance level begins to deteriorate and is modeled as a neglect tolerance curve (see Figure 1). In order to maintain an acceptable level of performance from the robot, the human must again turn his/her attention back to the robot before the robot performance degrades too far.

Acceptable frequencies and durations of human-robot interactions can be found using this method. By changing the minimum acceptable performance level, the necessary interactions change, as well as the robot's average performance. As an example, consider decreasing the minimum acceptable performance level shown in Figure 3. When this is done, the robot can be neglected longer before the human must interact with it again. Thus, the frequency of interactions between the human and the robot decreases. Additionally, changing the frequency of interactions may also affects the duration of the interactions which must occur. Therefore, lowering the minimum acceptable performance level decreases the operator's workload. However, observe that lowering the minimum acceptable performance level also decreases the robot's average performance. Likewise, increasing the minimum acceptable performance level increases both operator workload and robot performance,

The above method allows for robot performance, which is the robot's average performance over an interaction cycle, to be compared with a time-based workload metric called *Robot Attention Demand (RAD)* [9]. The RAD is given by $\frac{d_{\text{on}}}{d_{\text{on}}+d_{\text{off}}}$, where d_{on} is the average time spent servicing the robot and d_{off} is the neglect time. If the time the user spends servicing the robot is large compared to the time the user spends neglecting the robot, the workload, or RAD, is high. In contrast when the time spent servicing the robot is small compared to the time spent neglecting the robot, the workload is high. The most useful interaction schemes offer low workload and high performance.

4 Extension to Multiple Robots

The previous section described how neglect tolerance and interface efficiency measures can be obtained for single-robot systems. In this section we describe a method using these measures to predict the performance of multi-robot systems.

Let π_i be the interaction scheme employed by robot i and let R_i be the set of interaction rates available to robot i that cause the robot's expected performance to never drop below a certain threshhold (See Figure 3). Since $r \epsilon R_i$ represents both a frequency and a duration of interactions, we can encode each $r \epsilon R_i$ as an ordered pair $(d_{\text{off}}, d_{\text{on}})$, where d_{off} and d_{on} are defined as before. Let K, in the case of an n-robot team, be

$$K = R_1 \times R_2 \times \cdots \times R_n. \tag{1}$$

Hence, K is a set of n-tuples representing all possible combinations of interaction rates for n robots. Then, let K_j be a specific n-tuple in K as indexed by j, $K_{ji} \epsilon R_i$ be the interaction rate for robot i as defined by K_j, and $\pi_i(K_{ji})$ be the average expected performance of robot i employing interaction scheme π_i.

From these variables we define a function $F(\pi_1, \cdots, \pi_n, K_j)$ to be the performance of the system when interaction rate K_{ji} is used for each robot i. Formally,

$$F(\pi_1, \cdots, \pi_n, K_j) = \frac{1}{n} \sum_{i=1}^{n} \pi_i(K_{ji}) \tag{2}$$

Since we restrict ourselves to the case in which the human operator can only interact with one robot at a time, K_j is considered *legal* only if it is possible to interact with no more than one robot at a time and still fulfill the interaction requirements of each K_{ji}. Thus, the sum of the *RAD*'s corresponding to each K_{ji} in K_j may not exceed 1.0 to be considered legal.

We assume that the human operator will naturally seek to optimize the overall performance of the robot team. Thus, the predicted performance *pp* of the robot team will occur when the K_j is chosen that maximizes team performance. Therefore, we have the following constrained optimization problem:

$$pp = \max_{K_j \text{ is legal}} F(\pi_1, \cdots, \pi_n, K_j). \tag{3}$$

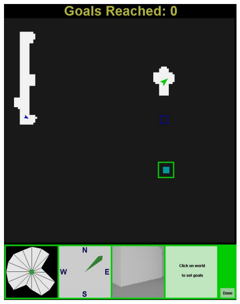

Figure 4: Snapshot of the user interface used in the experiments.

We note that $\pi_i(K_{ji})$ is a percentage of the performance level that the robot would obtain if it operated absolutely perfectly. Therefore, pp is also a percentage.

The above method makes several assumptions. First, it assumes that the operator can only interact with one robot at a time. Second, it assumes that the tasks that any two robots in the system perform are independent of each other. Third, it requires that measures of neglect tolerance and interface efficiency be obtained for the task in question.

5 An Example

In this section, we provide an example, performed in simulated worlds, that validates the usefulness of the prediction algorithm. To do so, we first describe a user study performed to obtain measures of neglect tolerance and interface efficiency for two interaction schemes. Second, we predict performance for 3-robot teams in a similar task and compare these predictions with actual results obtained from a second user study.

5.1 Finding Neglect Tolerance and Interface Efficiency

In the first user study, human-robot teams were asked to perform a goal-finding and exploration task. Operators were shown a grid-based map of the explored areas of the world. The unexplored portion of the world, however, was left blank on the map. The positions of the robots and their goals were also shown in the world, along with the sensory information of the robot being serviced by the operator. Figure 4 shows the GUI presented to the users in the experiments. The following two interaction schemes were employed by the robots.

P2P: A point-to-point interaction scheme. With this interaction scheme, the operator gives the robot instructions of what to do at the next intersection. The operator uses a mouse to click buttons on the GUI to indicate what the robot should do next. The robot uses its sonars to determine if it is currently in an intersection or not. While the robot is unable to move in the direction indicated by the user, it continues moving forward. When the robot is able to move in the direction indicated, it takes the action and resets the next command to straight ahead. It continues moving forward until the human issues a new command.

ROI: A region-of-interest interaction scheme. With this interaction scheme, the operator uses a mouse to drop a goal marker someplace in the environment. The robot moves towards the marker by recognizing decision places in the environment and generating its own internal map of the environment using algorithms from [7]. The robot uses this internal map to plan a path to the marker. If the area near the marker has not been explored, the robot estimates which path will most likely lead it there.

The measurement technology mentioned in section 3 and described in more detail in [2, 3] was used to estimate the neglect tolerance and interface efficiency of P2P and ROI. Two secondary tasks were used to force the operators to neglect a robot: (a) the control of a second robot and (b) two-digit arithmetic problems. In the user study, operators were allowed to interact with a robot as long as they felt necessary. However, once they chose to neglect the robot, they were not able to interact with it again for a specified time determined by the computer. Instead they were expected to perform the one of the two secondary tasks. This allowed the domain space of the random processes $V_N(P2P)$, $V_S(P2P)$, $V_N(ROI)$, and $V_S(ROI)$ to be sampled thoroughly.

Thirteen subjects participated in this user study. The users were trained on the interaction schemes and then performed six five-minute sessions during which data was gathered. Each session took place in a different world. Each world was classified as one of three different complexities, depending on the number of dead ends which the world contained. The mean of the random processes obtained from the data are shown in Figures 5 and 6 for $P2P$ and ROI respectively.

In Figure 7, various levels of RAD are plotted against average robot performance for the two interaction schemes at the three complexity leveles. These graphs illustrate the tradeoff that occurs between RAD and robot performance. It is important to observe that there appears to be a "sweetspot" for interaction rates for each interaction scheme. At a certain RAD robot performance peaks, after which increasing the percentage of time interacting with a robot only hinders its performance.

5.2 Predicting Team Performance

The measures of neglect tolerance and interface efficiency for the two interaction schemes were then used to predict, using equation 2, the performance of teams

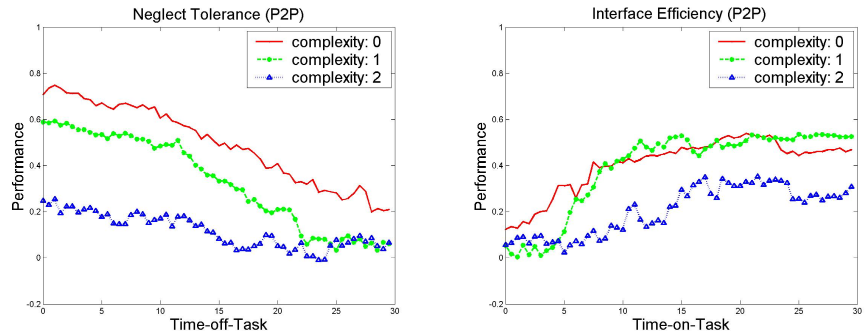

Figure 5: Plots of the mean of the random processes $V_N(P2P)$ and $V_S(P2P$.

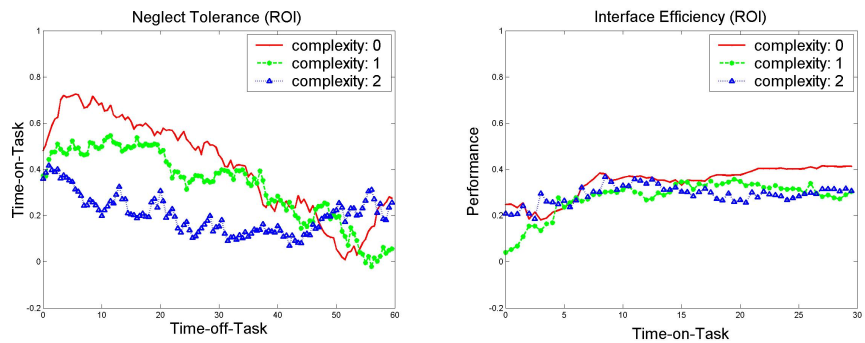

Figure 6: Plots of the mean of the random processs $V_N(ROI)$ and $V_N(ROI)$.

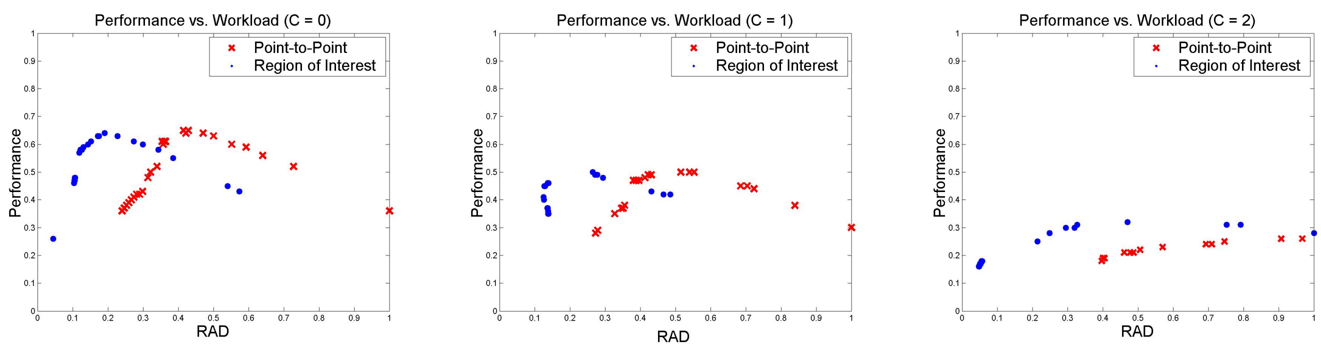

Figure 7: Comparison of the P2P and ROI interaction schemes in terms of RAD and performance for the three levels of complexity. Note that with each set of points performance peaks, after which increasing the operator workload for that robot hinders its performance.

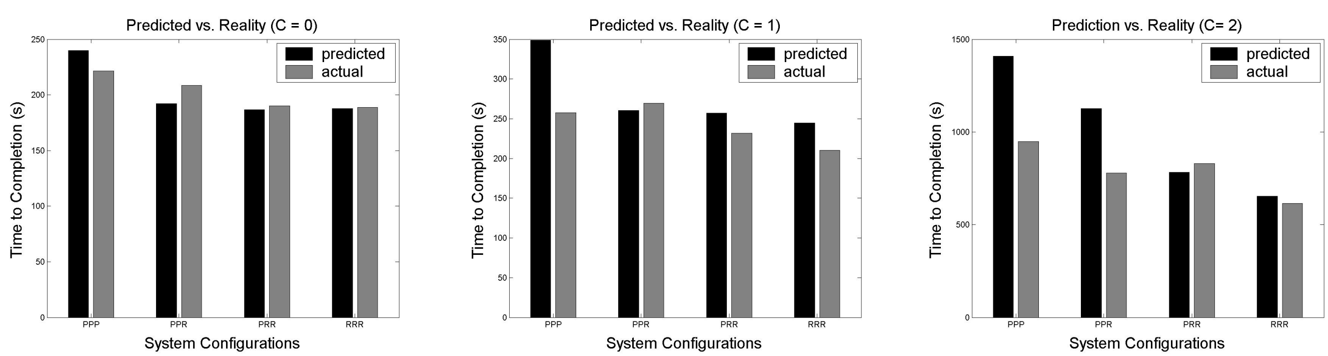

Figure 8: Comparisons of prediction and actual performance times for three world complexities.

with a human operator and three robots. Using different combinations of the interaction schemes, four different robot teams, or system configurations, were formed. They are called PPP, PPR, PRR, and RRR, P standing for a robot employing P2P, and R standing for a robot employing ROI. Since the performance prediction algorithm returns a percentage rather than a time, we converted the percentage into a time in seconds. This can be done by determining the average distance that must be traveled by a single robot during a session, divided by the robot's average speed. This average speed the maximum speed that the robot can travel (30 inches per second in this case) multiplied by the performance predicted by the prediction algorithm.

A second user study was conducted to determine the accuracy of these predictions. The task performed by the human-robot team was similar to that performed in the first study with a few exceptions. Since the user controlled three robots, three different goals were present at a time. Any of the three robots could collect any of the three goals. When a goal was collected, another goal appeared. The session concluded when nine goals had been gathered. During a session, the user could interact with any of the three robots at any time by clicking on that robot in the map of the world. The test was conducted with 23 users, each performing six sessions. For each world complexity and system configuration, 9 to 15 samples were obtained. The average of these times is plotted against the predicted performance in Figure 8.

In general, Figure 8 shows that the more the ROI robots in the system, the quicker the human-robot team completed a mission. This is true of both the actual and predicted results. The figure also shows that the prediction algorithm adequately predicted the performance of the robot teams in all cases except when the mission got very difficult. This occurred in complex worlds with system configurations that require high operator workload. In these situations, the actual performance is much better than the algorithm predicted. Such a result is not surprising, since users implemented coping strategies in these situations which violated some of the assumptions made by the algorithm. Even still, the algorithm was able, in general, to predict which combination of interaction schemes yielded the highest team performance.

6 Summary

In this paper, we described an algorithm for predicting the performance of human-robot teams. The algorithm is built on the principles of neglect tolerance and interface efficiency, and can be useful for determining the effectiveness of human-robot interactions in multi-robot teams.

While the algorithm was shown to be useful, it has several limiting assumptions, and also requires that a large number of user studies be performed to obtain the neglect tolerance and interface efficiency of each interaction scheme used by the system. We leave these issues for future work.

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