Sharing Autonomy of Exploration and Exploitation via Control Interface

Aiman Munir Ramviyas Parasuraman

***Abstract*—Shared autonomy is a control paradigm which refers to the adaptation of a robot's autonomy level in dynamic environments while taking human intentions and status into account at the same time. Here, the autonomy level can be changed based on internal/external information and human input. However, there are no clear guidelines and studies that help understand "when" should a robot adapt its autonomy level on different functionalities. Therefore, in this paper, we create a framework that helps to improve the human-robot control interface in allowing humans to adapt the robots' autonomy level as well as to create a study design to gather insights into human's preference to switch autonomy level based on the current situation. We create two high-level strategies - Exploration to gather more data and Exploitation to make use of current data - for a search and rescue task. There two strategies can be achieved with human inputs or autonomous algorithm. We intend to understand the human preferences to the autonomy levels (and "when" they want to switch) to these two strategies. The analysis is expected to provide insights into designing shared autonomy schemes and algorithms to consider human preferences in adaptively using autonomy levels of certain high-level strategies.**

I. Introduction

Human-robot teams have been increasingly used to complete missions such as urban search and rescue [1], post-disaster intelligence gathering [2], border patrol [3], social interactions [4], etc., which has led to the exploration of human-robot interaction. Historically, robots have been employed as subordinates for the accomplishment of human missions. With the introduction of sophisticated algorithms and the improvement of robots' capabilities, autonomous robots have become more popular. Automation reduces human workload by performing the continuous and repetitive tasks accurately. The role of each participant in the human-robot team defines their authority and functionality in completing the assigned task. Depending on the role assigned to the robot, its automation level can vary significantly from manually teleoperated to completely autonomous, as given by [5], [6]. Autonomy level is a determining factor for human-robot interaction in terms of robot's performance and the level at which this interaction takes place [7].

Shared autonomy is a control paradigm which refers to the adaptation of robot's autonomy level in dynamic environments while taking human intentions into account at the same time [8]. The autonomy level is changed based on internal/external information and human input. Only robot is responsible for the adaptation based on the acquired information.

Trust is a key factor affecting the performance of human-robot team and human's reliance on automation. There are many definitions of trust in the literature, but we would use the definition presented by [9] as it includes human attitude in uncertain situations. It defines trust as "the attitude that an agent will help achieve an individual's goals in a situation characterized by uncertainty and vulnerability". For the success of any human-agent mission, it is critical to avoid misuse or disuse of the system, i.e., to calibrate the appropriate trust level. [10] presents an adaptation framework for computation of robot policy aligned with human preference while retaining trust. [11] mentions trust as an important aspect of mobile assistance robots and relates it to user's safety and comfort. Hence, being able to understand how the human's preference to autonomy level affects operators' trust level is vital to shared autonomy.

Despite the importance of robot's autonomy level and trust for shared automation, there has been little research on how change in robot can affect the trust level, particularly post-disaster scenarios. To make the robot adjust its autonomy level based on human intentions, we need to collect data on human preferences in various aspects of autonomy. The purpose of our paper is to provide this supporting data and research to the shared robot autonomy algorithms. We consider a real-world search and rescue scenario, where a human-robot team has no previous knowledge of the environment aside from its dimensions. Robots are remotely controlled by humans with the purpose of gathering intelligence before rescue teams can choose which locations to visit in the area. Our objective in this paper is to investigate human preferences for the level of automation, based on the performance of the human-robot team and trust in the system.

The contributions made through this study are as follows:

- We create a control interface framework to simulate a search and rescue operation in localizing human victims through their radio beacon (e.g., phone) sources. The framework will allow changing the autonomy level of two high-level strategies/tasks (Exploration and Exploitation) during the mission.
- We analyze human preferences and priority for the autonomy levels of high-level strategies during the tasks. We study the human-agent team performance through quantitative metrics and plan to examine qualitative metrics, including human's trust on the robot in the context of automation level.

An autonomous multi-robot intelligence gathering system is presented in [2] for post-disaster scenarios with unreliable communication and limited human involvement. To assign tasks to the robots and ensure safe operation, the operator employs a graphical user interface. Taking inspiration from this study, we use mobile signal to locate victims in a post-disaster scenario. In comparison to the former, our study

The authors are with the Department of Computer Science, University of Georgia, Athens, GA 30602, USA. Authors email: {aiman.munir,ramviyas}@uga.edu

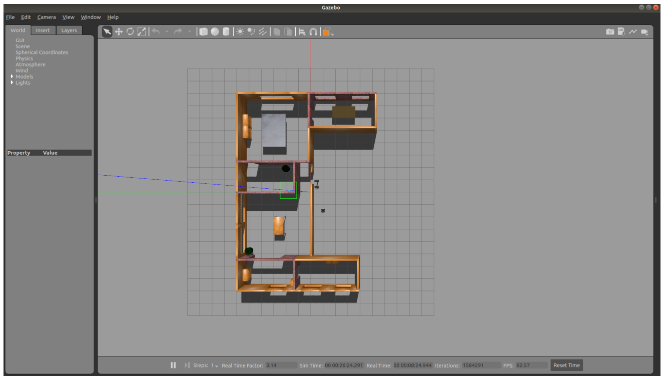

Fig. 1. The Gazebo office world used for our simulations.

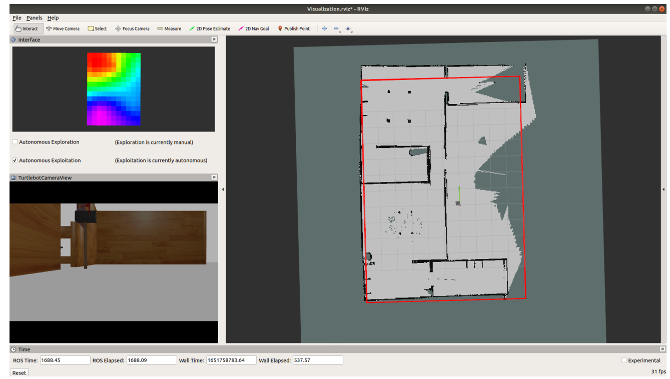

Fig. 2. The image of Rviz window. Left Panel: shows real time sensor (Wireless signal RSSI) map, interface, and camera view from the turtlebot robot. Right Panel: shows the occupancy map, turtlebot's current position, and the goal location using green arrow. The interface contains options for choosing the "Exploration" and "Exploitation" strategies manual/autonomous. In manual mode, the users will specig=fy the waypoints (to explore) or mark the source location on the sensor data (to exploit). In autonomous mode, the robot will use its algorithms to autonatically find waypoints for exploration (using typical informative path planning algorithm e.g., [21]) or present the source location by analyzing the peaks of the sensor data predicted over the entire map area (using Gaussian Processes Regression algorithm used in [22]).

investigates human preferences for autonomy level and its influence on trust in robots, whereas [2] evaluates the proposed system. Exploration and exploitation are widely used terms in information sampling [12], informative path planning [13], target tracking and localization [14], mapping environmental phenomenon [15], environmental monitoring [16], sensor coverage [17], source localization [18], and search and rescue [19] among others.

Exploration refers to accumulating sensor data samples from previously unexplored areas to reduce uncertainty, while exploitation implies determining the next target point based on the best information from the current estimates of the sensor data. Our study uses the task of exploring and exploiting the human victims after a post-disaster scenario.

Surveys conducted in [20] determine the attitudinal preferences of humans toward autonomous agents and robots as tools and the effect of autonomy level on attitudes. Unlike this article, our study assesses human preferences using simulation experiments instead of surveys, which can illustrate how robots and autonomy levels will be useful in realistic settings. Furthermore, we are also interested in evaluating how autonomy level affects trust, which is a major design goal for human-robot collaboration.

II. Experimental Design and Implementation

We consider a post-disaster scenario for the analysis of human preferences for autonomy and its impact on trust in a search and rescue mission. We have developed the simulations using the Robot Operating Systems (ROS [23]) Gazebo simulation framework. An RViz based interface is employed to render 3D sensor data visualizations and on-screen interaction. We considered an 11 m $\times$ 15 m simulated area. Until the robot's battery is depleted, it makes a map of the unknown environment using a state-of-the-art mapping algorithm, i.e., SLAM (Simultaneous Localization and Mapping). Besides mapping the environment, the robot also measures the signal strength of the wireless signals from the target location chosen autonomously (based on the informative function) or given by the operator via interface. We have used the PointCloud2 Library in ROS to visualize the RSS (received signal strength) map received through the GPR (Gaussian Process Regression) based on the work in [22].

The environmental map, real-time RSS map, current and target robot's positions and robot's path are all visualized using RViz interface. With each new goal location reached by the robot, the Gaussian process regression is trained, the intensity values of the signals are predicted. The robot's starting location and battery timing were kept fixed for all scenarios. The ground truth for each radio beacon was generated as per the equation: $RSS = RSS_{d0} - 10n\ln(d) + \chi_g$, where $RSS_{d0} = TX_{power} - 20\ln(\frac{3}{4\pi * f})$ is the signal reference power at $d0 = 1m$, f is the signal frequency (2.4GHz), n is the path loss exponent ($n = 3$), d is the distance between the signal source and receiver, χ_g is a Gaussian distribution with zero mean and a variance ($0.65dBm^2$) to represent fading/noise in signals.

Figs. 1 and 2 shows the simulation world used and interface used for experiments, respectively. The red bounding box in the rviz interface shows the region of interest. Only the dimension of the region of interest are known beforehand to replicate the real-world scenario.

A. Experiment Scenarios

The following scenarios will be considered in our study.

1) Manual Explore and Exploit - The user will assign locations to the robot for exploration and exploitation. That is, the user will give the waypoints to explore new areas, as well as the users will interpret the sensor data themselves in understanding where the sources could be.
2) Manual Explore and Autonomous Exploit - Users will specify the locations of where to explore next, and the robot will exploit the sensor data (predict the source

locations) based on the gathered information during exploration.
3) Autonomous Explore and Manual Exploit - The robot will perform exploration to gather information about the sensor map, and based on that information, the operator can establish exploitation goals.
4) Autonomous Explore and Exploit - The robot performs exploitation to collect information on the sensor map and exploitation to locate sources based on acquired information.
5) Adaptive Interface - The user can switch between manual/autonomous exploration and exploitation, any time during the experiment.

In the first four scenarios, we will examine about operators' preferences when roles are fixed; on the fifth scenario, we will discover how operators respond when they have a choice between manual and autonomous task execution. The fifth scenario will be useful to understand "when" the human want to change autonomy level by holistically considering the biases they exhibit (using the other four scenarios) as well as based on the current performance levels.

B. Evaluation Metrics

We consider the following performance metrics:

1) Task Performance: We consider task performance as the ratio of the number of victims/sources localized and total number of victims present.
2) Workload: To determine the effect of autonomy level on user load, we will use NASA_TLX questionnaire [24]
3) Trust: We will use a 7 point Likert 5-point scale [25] to determine user's trust in the robot
4) Adaptability: The user's preference for robot's adaptability of autonomy level will be determined by using a 5-point Likert scale.

User surveys will be conducted before and after each experiment scenario. Once the experiment is completed, performance will be measured only once, both in terms of exploration and exploitation.

C. Experiment Objectives and hypothesis

We aim to accomplish the following objectives through the planned experiments:

- Determine which experiment scenario provides the best efficiency and task performance.
- Analyze users' preferences for autonomy level across all experiment scenarios.
- Assess how autonomy levels affect operators' trust.
- Identify the situations "when" the robot should mediate the autonomy level.

D. Preliminary Work

Our research is still in its early stages, and we still need to recruit participants for qualitative analysis. Using the "Autonomous Explore and Autonomous Exploit" strategies, we have conducted experiments to demonstrate how our approach works. This provides a baseline of the current autonomy performance so that we can analyze how human may use these autonomy algorithms during their mission.

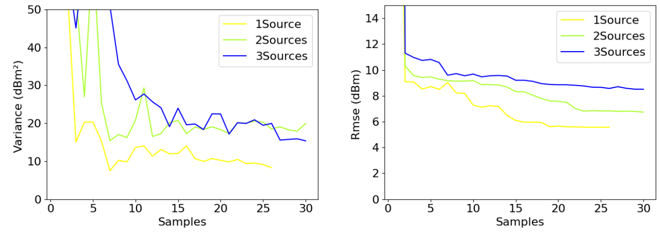

Fig. 3. Average change in Variance and RMSE over 5 trials for different number of sources

TABLE I
NUMBER OF SOURCES LOCALIZED IN EVERY TRIAL.

		Number of localized Sources				
		T1	**T2**	**T3**	**T4**	**T5**
True Number of Sources	**1**	1	1	1	1	1
	2	2	1	2	2	1
	3	2	2	1	2	2

1) Autonomous Exploration Results: To analyze exploration, we consider two key performance metrics: RMSE (The root mean squared error between the predicted mean information of the Wi-Fi signal strength through the GPR and the simulated Wi-Fi signal ground truth information) and the variance (The confidence bounds of the predicted values given by the GPR, where variance refers to the average variance of the region of interest). Ideally, we would like to see both RMSE and Variance as low as possible for better exploration performance indication.

Fig 3 shows the average change in variance and RMSE with respect to number of samples. The purpose of exploration is to reduce the RMSE and variance, so it can be seen that the robot was quite successful in reducing both the variance and the RMSE.

2) Autonomous Exploitation Results: The goal of exploitation is to localize all the source with less localization error. Tables I and II shows the number of sources that were localized by the robot and the localization error in meter for each trail for different number of sources. As the number of sources increased, the localization accuracy decreased. This may be because it is running online SLAM and most of the time it chooses routes involving longer distances. Furthermore, the robot cannot collect more than 30 samples on average from an area of $165m^2$, which makes it unable to accurately localize the sources.

III. CONCLUSION

We have developed a framework that can act as a data generator to collect valuable data about humans' preference for autonomy and its effect on trust, as well as provide guidelines for shared autonomy algorithms. Adaptation is an essential part of shared autonomy, and our study is intended to help understand "when" to adapt the robot's autonomy level to better support the human goal while maintaining trust.

TABLE II
LOCALIZATION ERROR(M) FOR ALL SOURCES LOCALIZED IN EVERY TRIAL. FOR MORE THAN ONE LOCALIZED SOURCE, EACH ERROR IS SEPARATED BY COMMA(,)

		Mean Absolute Localization Error (m)				
		T1	**T2**	**T3**	**T4**	**T5**
Number of Sources	**1**	2	0	3	4	2
	2	1,2	1,-	2,1	1,3	1,-
	3	2,2,-	1,2,-	1,-,-	1,3,-	0,3,-

Currently, we have only conducted experiments on one ”autonomous” scenarios discussed in our study. Even though the robot is technically capable and was able to perform quite well in exploration task, the performance for exploitation can still be improved. It still requires human collaboration to accomplish the task fully. Human can give more preference to the areas where the sources are located to reduce localization error, or human can explore more region to gain information about the victims. Understanding the need for adaptation will be easier through this necessity of human cooperation.

In our planned work, we will seek to answer the following hypotheses: 1) the human operators will prefer the autonomous robots for both exploration and exploitation if they perform well; 2) the level of trust between users and robots is correlated with the task performance; 3) the operator would like the robot to adjust autonomy level if it gets stuck or cannot perform well.

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