Communicating via Augmented Reality for Human-Robot Teaming in Field Environments

Christopher Reardon[1], Kevin Lee[2], John G. Rogers[1], and Jonathan Fink[1]

***Abstract*— This work focuses on the critical problem of treating humans and autonomous robots as peer teammates for tasks performed in unstructured, uninstrumented environments. To accomplish this peer relationship, we propose to use the communication of information to the human and the autonomous robot teammate as a method of influencing their behavior. We use augmented reality technology to achieve a bi-directional communication of information between teammates. We outline multiple strategies for information communication from the autonomous robot to the human teammate. We examine these alternatives in the context of human-robot cooperative exploration of an unknown and uninstrumented environment. We present results from three experiments which show potential influence on human task performance in cooperative exploration.**

I. Introduction

Enabling human-robot cooperation in unstructured and uninstrumented environments, specifically where humans and robots perform a task as equal teammates, is an important and challenging class of problems. Solutions to this class of problems could have significant impact on many application domains, such as search and rescue, environmental monitoring, disaster response, and military operations.

Humans in such cooperative human-robot interaction tasks are most often in a supervisory role [1]. Even teamwork-centered approaches to adjustable autonomy give control for some specific activities to autonomous agents and other specific activities to humans teammates to enable cooperation [2]. In many human-robot teaming scenarios where the teammates are performing the same task, the robot is often expected to adapt or defer to the human teammate at points of uncertainty or cognitive load [3]. The ability for human and robot teammates to work cooperatively as equal teammates has received some attention [4], but we are interested in extending into situations where autonomous robots and humans are performing the same task, in a similar or overlapping role, in unstructured and unknown environments.

The communication of information fundamentally influences the decisions and behavior of intelligent agents. By varying the quantity and quality of the information communicated, the behavior of teammates consuming that information can be affected. The issue of what information to communicate between teammates and when is particularly important in multi-agent collaborative tasks in uninstrumented, unknown environments. For example, research has shown how using local, implicit information to reduce interference [5], how good performance can be achieved without communication if the number of teammates is known [6], and how in a competitive team search setting larger teams are hindered more than smaller teams in a situation where neither can communicate [7].

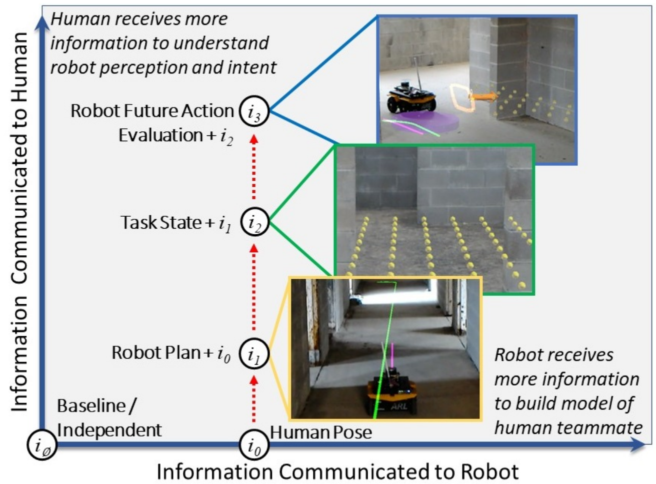


Fig. 1: Teammate information communication overview. The x-axis represents information about the human teammate communicated to the robot, which allows the robot to better model the human teammate. The y-axis represents information about the robot perception and intent that is communicated to the human teammate. At baseline $i_\emptyset$ is no communication. This paper implements i_0 and focuses on three points on this spectrum, denoted by i_1, i_2, and i_3.

We believe that information communicated via augmented reality (AR) presents an opportunity to influence the behavior of human teammates in human-robot cooperative tasks with the potential to improve task performance. In this work, we leverage the recent emergence of AR devices to both collect information from the human teammate and present information via augmented reality. Information from the human can enable improved decision making by the robot teammate. At the same time, this system will allow us to control the information presented to a human, influence the human's model of the robot's knowledge and behavior, and shape the human's performance. In this way, we treat the human and robot teammates as peer members of the cooperative team, and seek to influence each through information communication.

[1]Army Research Laboratory, Adelphi, MD 20783, USA {christopher.m.reardon3, john.g.rogers59, jonathan.r.fink3}.civ@mail.mil

[2]Army Research Laboratory Research Associateship Program administered by Oak Ridge Associated Universities. klee23456@gmail.com

There are several technical challenges to communicating and visualizing information between a robot and a human teammate. These challenges include establishing an accurate alignment (e.g., rigid body transform) between robot and human frames without external instrumentation, communicating shared information between the teammates in the context of that transform, and enabling the visualization capabilities subject to constraints on the AR device. We present a set of enabling technologies to overcome these challenges and accomplish the communication of information via AR. We leverage those enabling technologies to demonstrate that by manipulating the information communicated to the human in this manner, we can influence behavior. We specifically examine this influence in a cooperative exploration task in unknown, uninstrumented environments.

Given these challenges, we believe information communication in human-robot team collaborative tasks can be broken down is into two primary axes along the lines of communication (Fig. 1):

1) Communication of information to the robot that allows the robot to build a better model of the human to shape robot decision making, and
2) Communication of information to the human that allows the human to understand the the robot, such as the *robot's current plan*, *state of the exploration task*, and *how the robot is evaluating future actions*.

In the context of cooperative exploration, we note that for 1) communication and its impact on the robot's model and decision making can be engineered to enhance predictability, while for 2) because the human teammate is consuming the information, the information presented to the human can be used to shape the human's mental model and future actions with less transparency. For defining the communicated information strategies of 2), we draw inspiration from previous work on situational awareness [8], particularly in the context of human-robot teaming [9], whose model defines three levels of situational awareness: purpose and perception, reasoning and belief, and projection to future state.

To examine the impact of these dimensions on team performance, in this work we present the design of a system and technology to explore communication for the human-robot cooperative exploration scenario. We demonstrate this system in three real-world experiments, where the human and robot cooperatively explore an uninstrumented environment. Our results show that communicating information about plan, task, and future action evaluation allows us to influence human performance and enables human-robot cooperative exploration in uninstrumented environments. We present results from different communication strategies and analyze their strengths and potential weaknesses.

II. Overview

Here, we present an overview of the concepts and main components necessary to enable bi-directional information communication via AR for collaboration in unstructured, uninstrumented environments.

A. Cooperative Exploration

Human-robot cooperative exploration is an important application for domains such as search and rescue, environmental monitoring, and military operations. The need for autonomous robots to perform better alongside humans in disaster and search and rescue scenarios in particular is essential [10], [11]. In these potentially time-critical applications, humans and robots will be expected to work together to coordinate their search patterns to find their targets more quickly than each teammate acting alone. While information-theoretic exploration [12], [13], [14] and cooperative multi-robot search and exploration [15], [16], [17] are areas of ongoing research, technologies that enable human-robot cooperative exploration are not well-studied.

Challenges for cooperative exploration include balancing implicit vs explicit communication of local and global information, bandwidth, and scaling to larger teams. A human teammate introduces additional challenges, such as issues of understanding the human's model of the task, providing contextually-relevant information to shape that model, and predicting the human's actions in order to adapt the robot teammate's strategy accordingly.

We propose a cooperative human-robot team where the human is equipped with an augmented-reality head-mounted device (AR-HMD), and must explore an unknown environment with a robot teammate. The AR-HMD and robot both have on-board simultaneous localization and mapping (SLAM) capabilities. The robot searches autonomously, using a frontier- and information theoretic-based search strategy, such as in [18].

B. Frame Alignment in Uninstrumented Environments

To examine the impact of communication, the human and robot must share information about their proprioceptive states. Because each are performing SLAM independently, a critical initial step is to compute the rigid body transform that allows us to represent information in each other's respective frames. A simple solution to this problem is to instrument the environment, e.g., with vision-based markers or motion capture systems, and directly compute the transforms between the human and robot's frames. However, we envision this technology being particularly impactful in applications beyond laboratory and factory settings e.g., in cooperative search and exploration applications in disaster sites where such instrumentation would be impossible.

Therefore, we leverage the approach presented in [19] to align the coordinate frames of the robot and human. We assume that both the robot and the AR-HMD generate a geometric representation of the environment in point cloud format. We compute the homogeneous transformation matrix between the robot and human point clouds $T_r^a \in SE(3)$, where the subscripts r and a represent the robot and AR-HMD (human) frames, respectively. We likewise define x_r and $x_a \in SE(3)$ as the starting poses of the robot and human, respectively. Solving for T_r^a is a multi-step process:

1) An initial estimate of T_r^a is generated by the human, who uses the AR-HMD interface's pointing and ges-

ture recognition to place an AR marker indicating the robot's initial pose x_a in the AR-HMD frame.
2) The reference-frame transformation is initialized as $T_r^a = x_a \cdot x_r^{-1}$.
3) The Iterative Closest Point (ICP) algorithm [20] is applied to this initial coarse estimate to refine the frame alignment.
4) The transformation is recomputed online as the robot and the human-worn AR-HMD move throughout the environment.

C. Compositing Heterogeneous Maps

Central to the communication of information for cooperative exploration (or many tasks where teammates are maneuvering in the same environment) is the fusing of map information.

In our application, we fuse map information generated by a mobile ground robot equipped with a LiDAR sensor and an AR-HMD performing vision-based SLAM to generate a composite map.

The mapping system used on board the mobile robot is based upon OmniMapper [21]. This system is composed of a back-end pose graph smoothing engine and a front end module which inserts vertices and edges in the graph. Pose graph vertices represent the robot's location and the associated sensor measurements, such as a 3D point cloud, observed at that time. Pose graph edges consist of ICP corrected relative pose measurements for subsequent adjacent vertices. Additionally, loop closure measurements are inserted when ICP matches are made for point clouds associated with vertices from much earlier in the robot's trajectory which appear to be overlapping with the current observations. These types of measurements enable the mapping system to correct accumulated error from incremental adjacent measurements.

Sensor measurements associated with pose graph vertices are used to generate local occupancy grid maps by iterating through the point cloud and setting an obstacle for points which fall within a height filter. For each of these points, an line of grid cells to the sensor's origin is cleared. Each of these local occupancy grid maps is then combined using the optimized robot trajectory using negative log-odds, which counts obstacle observations minus clear observations and generates an occupancy probability map.

The HMD utilizes a proprietary SLAM system to track the device's motion and generate a model of the environment. This procedure provides a sparse point cloud representation of the modeled area. As we do not have access to the internals of the SLAM implementation used on-board the HMD, we must first convert the point cloud into an occupancy grid so it can be composited with the robot's map to generate a unified global view. The point cloud from the HMD is converted to an occupancy grid by setting cells to be obstacle when the maximum height of all points from the cloud which fall within a vertical column over the cell exceeds a threshold of $7cm$. Conversely, when the maximum height falls below this threshold, the associated grid cell is cleared to free space.

The occupancy grid converted from the HMD's point cloud is composited onto the robot's occupancy grid using the relative transform found in Section II-B. The HMD occupancy grid information is only composited into the unknown area of the robot's occupancy grid where the robot has not mapped.

This fused composite map ultimately allows the each teammate to leverage the exploration efforts of the other in its own decision making.

D. Visualization of Robot Teammate's Information

In order to explore communication of robot information to the human, capabilities were constructed to translate that information into a format for visualization via AR.

In general, information is presented as semi-transparent geometric objects and text to the human wearing the AR-HMD. Based upon our use of the ROS framework (see Sec. IV-A), we implemented visualization capabilities for all RViz[1] visualization objects. In this process, we made modifications to enhance usability and to address technical challenges.

Due to the size of the occupancy grids, several actions were taken to reduce their impact on render time and bandwidth. The occupancy grid was naively downsampled before being broadcasted. In addition to lowering the still significant bandwidth cost, reducing the number of objects to represent the costmap helped with information overload.

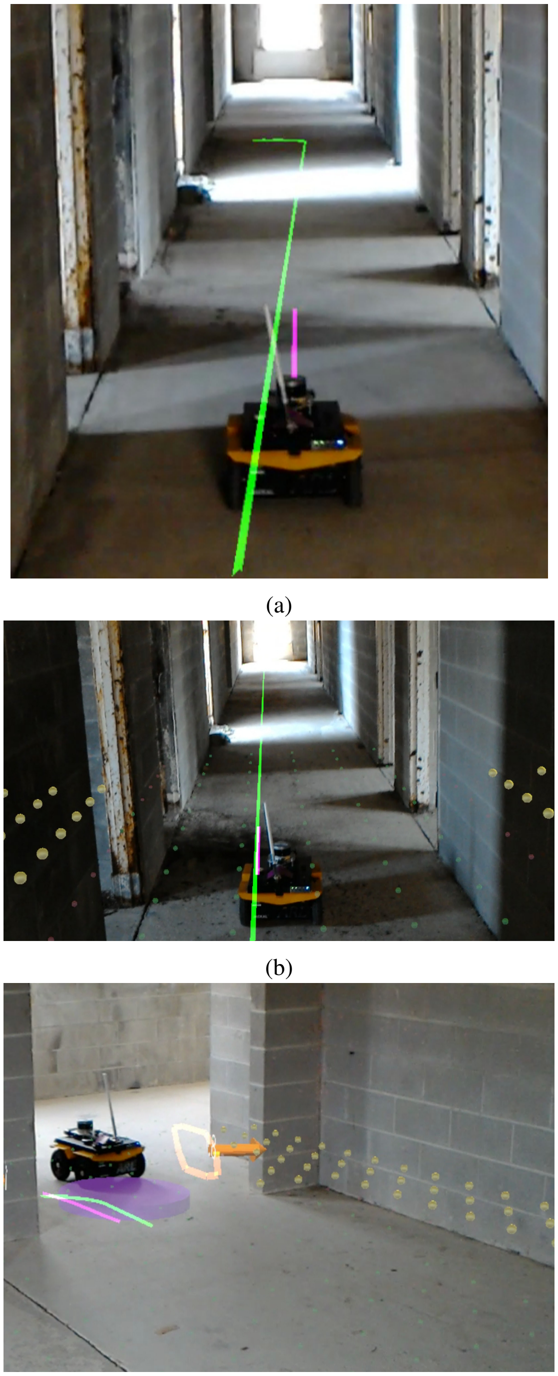
Signal strength and bandwidth are rarely optimal in field environments, and this made receiving the costmaps at a high frequency challenging for the AR-HMD. To address this, along with the downsampling, only select portions of the occupancy grids were transmitted. Three areas were selected due to their importance: the area around the user, around the robot, and around the gaze location. Using only these locations as opposed to the entire grid created a healthy balance between bandwidth usage and showing useful information to the user. Using instanced draw calls would be a future improvement that could increase the number of rendered cells significantly, perhaps even removing the need to split the costmap.

III. Approach

In the context of cooperative exploration (Sec. II-A), we begin to address 1) from Sec. I - communication of information to the robot that allows the robot to build a better model of the human to shape robot decision making. We perform a first step in this direction by integrating the human's map (generated by the AR-HMD) with the robot's map for robot planning.

We show how our system is able to more deeply explore 2) from Sec. I - communication of information to the human that allows the human to understand the robot's plan, the state of the task, and the robot's information-theoretic decision making. To accomplish this, we use an AR-HMD to: A) Visualize the *robot's current plan* in the AR display, B)

[1] wiki.ros.org/rviz



(a)

(b)

(c)

Fig. 2: (a) *Communicating the robot's current plan*. The robot's planned path (green line) and computed kinematically feasible movement trajectory (purple line), as seen by the human through the AR-HMD. (b) *Communicating the current task state*. Explored unoccupied regions are faint green spheres. In addition to what is visualized in (a), explored occupied regions are faint red spheres, and unexplored regions are larger, yellow spheres seen behind the walls to the left and right of the robot. (c) *Communicating the robot's evaluation of future actions*. In addition to (b), the robot communicates unexplored frontiers (orange outlines) and goal points (purple circles).

Display the integrated human-robot map to the human via AR to help the human understand the current *state of the exploration task*, C) Further add information gain information and frontier selection decisions to the environment to convey *how the robot is evaluating future actions*.

A. Communicating the Robot's Current Plan

The robot's current plan is a trajectory from the robot's current position to its selected destination in $SE(3)$. The kinematically-feasible plan for the robot is generated using the Search-Based Planning Library [22].

An example of the visualization of this plan, as seen from the perspective of the human teammate wearing the AR-HMD, is shown in Fig. 2a. We represent the path to the human as a continuous sequence of line segments from the robot's current position to its goal. This sequence is updated live as the robot traverses the path, and the path is subject to replanning due to obstacles, slippage, etc. Both the global and local path are displayed to give a full representation of the robot's intent and planning.

B. Communicating the State of the Exploration Task

We communicate the state of the exploration task to the human using the AR-HMD. Fundamentally, the state of the exploration task is the amount of information that has been recovered by the team, i.e., the area that has been explored. We therefore represent this state as the area that has been mapped by the human-robot team.

The data structure that underlies this state is a 2D occupancy grid of resolution $0.1m$/pixel with values from 0 (unoccupied) to 100 (fully occupied). The method for generating this grid is described in II-C.

We present the occupancy grid to the human via AR as a collection of colored spheres at floor level. The spheres are colored by their occupancy grid value, with unoccupied tiles as green and occupied as red. Tiles with a value around 50 are viewed as unknown, and are yellow, more opaque, and significantly larger to draw attention to them. An example image from the AR-HMD perspective is shown in Fig. 2b. In order to limit the number of objects rendered on the AR-HMD, the grid is decimated before three sections are isolated for visualization: the area around the user, around the gaze location, and around the robot itself.

C. Communicating Robot Evaluation of Future Actions

As described in Sec. II, the robot's exploration strategy is frontier- and information-theoretic-based. Frontiers are defined as regions on the boundary between the explored map and unexplored space [23]. The selection of which frontier to explore next is based on an information gain metric that increases efficiency and accuracy [18]. In our communication strategy, frontiers are represented as orange outlines around small zones labeled with a utility value. The utility is a measure of information gain weighted against the robot's distance to the frontier. After identifying frontiers and potential information gains, the robot identifies a set of goal positions from which to observe those frontiers, visualized to the human via AR as purple circles. Example visualizations of the frontiers and goal positions are shown in Fig. 2c.

IV. Experiments

To demonstrate the impact of information communication between teammates, we conduct experiments using each of the communication strategies described in Sec. III. In these experiments, a researcher performs the role of human teammate, and the robot, human, and combined contribution to information gain is measured. A full-scale human study is a subject for future work.

For all experiments, the human and the robot perform cooperative exploration of the environment, the human teammate's AR-HMD information-based mapping information is communicated to the robot, and that information is composited into a unified map as described in Sec. II-C. The robot teammate is then able to identify and explore areas that still contain unknown information, i.e. areas that the team has not explored and mapped.

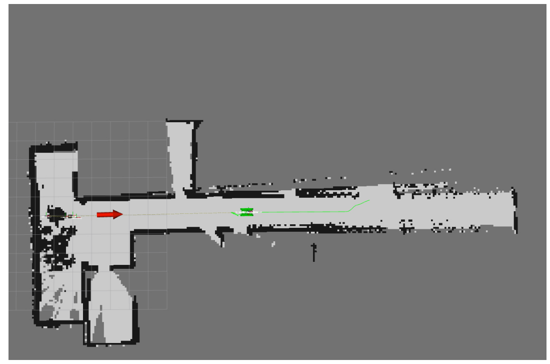
The communication strategies and corresponding experiments are organized such that increasing levels of information from the robot are added to the total information communicated to the human in each successive experiment. In the first experiment, the robot's current plan is communicated via AR to enable human understanding of robot intent (Sec. IV-B). For the second experiment, the current state of the exploration task, i.e. which areas are explored and which are unexplored, is also communicated via AR (Sec. IV-C). For the third experiment, the information about the robot's future plans, i.e. exploration frontiers and goal points to explore those frontiers, is communicated as well (Sec. IV-D). For each communication strategy, we measure the information gain by the human-robot team and present representative outcomes.

A. Hardware and Software

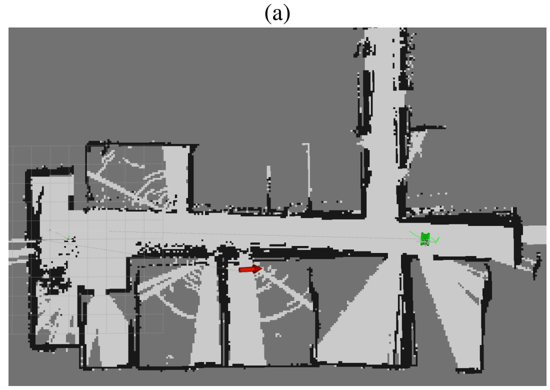
A Clearpath Robotics Jackal robot (Fig. 2a) performs cooperative exploration alongside a human experimenter in these experiments. The robot is equipped with a Velodyne VLP-16 LiDAR, Microstrain 3DM-GX4 inertial measurement unit (IMU) and an Orbbec Astra Pro camera. Custom software enables the robot to perform simultaneous localization and mapping (SLAM) and autonomous navigation as described in [24]. The AR-HMD worn by the human in these experiments is the Microsoft Hololens[2]. The Hololens performs vision-based mapping onboard using a sensor array of forward-facing cameras, whereas the robot uses the 360° LiDAR sensor.

The software used is implemented as a suite of C++, Python, and C# software modules. We leverage ROS[3] for messaging, interprocess communication, and common robotics libraries. We use ROS#[4] for Hololens-ROS communication with custom Unity extensions for visualization and mapping information. The Hololens has an onboard visual SLAM solution that outputs a 3D mesh-based map of the environment, which we translate into a point cloud and use for frame alignment and map compositing as described in Sec. II.

[2]microsoft.com/hololens
[3]ros.org
[4]github.com/siemens/ros-sharp



(a)



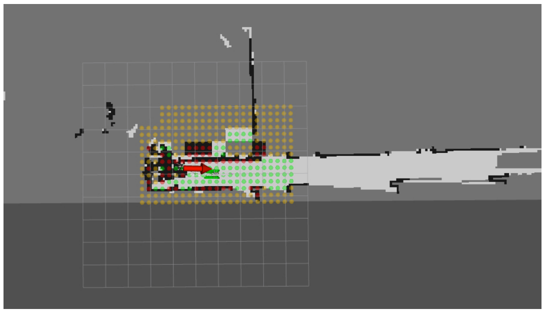
(b)

Fig. 3: Time-series results from communicating the robot's current plan as visualized in Rviz. (a) shows the human teammate (red arrow) following the robot (green rectangle) down a hallway similar to Fig. 2a. Shortly later (b), seeing through AR visualization of the robot's plan that the robot's intent is to proceed down the hallway, the human uses this information to decide to explore a nearby room that the robot did not enter.

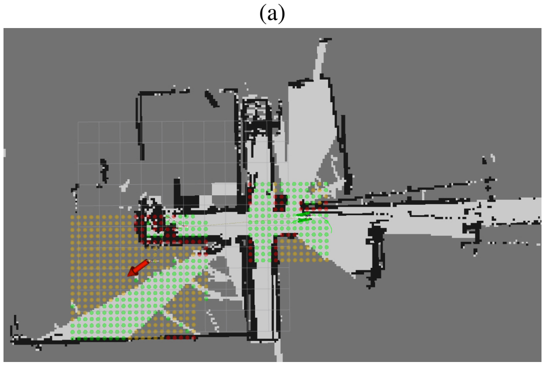
B. Communicating Robot's Current Plan Enables Intent Understanding

In this first experiment, the most basic level of information is shared to the human. The robot's current motion plan is visualized to the human as described in Sec. III-A. At any moment, the human teammate is able to explore areas that the robot is not currently planning to visit. Other than this current motion plan, it is up to the human teammate to maintain a mental model of the places the team has visited.

Using this information visualized via AR, the human teammate is able to infer the robot's intent in performing the exploration task. Figure 3 depicts representative results from this experiment. After entering the building, the robot teammate's information-theoretic-based planner selects a path down the center of the hallway (Fig. 3a). The human teammate is able to see that path (appearing very similar to Fig. 2a) and selects a room that the human did not see the robot enter (Fig. 3b).



(a)



(b)

Fig. 4: Time-series results from communicating the exploration task state as visualized in Rviz. In (a), the human (red arrow) and robot (green rectangle) have entered the building. In addition to the information displayed in Fig. 3, explored unoccupied areas are shown as green spheres, and explored occupied areas are red spheres. Unexplored areas are shown as yellow spheres. This is analogous to the AR depiction shown in Fig. 2b. Shortly later (b), the robot proceeds straight ahead, and the human moves to an unexplored area.

This experiment was performed in three buildings of similar size but different configuration. Information gains across all three environments are shown in Figs. 6a-c. We can observe that using this small amount of information, the human teammate is able to contribute moderately to the cooperative exploration task.

C. Communicating Exploration Task State Enables Cooperative Mapping

For the second experiment, we communicate information regarding the state of the exploration task to the human teammate as described in Sec. III-B. This is in addition to the robot plan information communicated in the first experiment. A depiction of this information is seen in Fig. 2b.

Using the information about the exploration task state, the human and robot are able to more cooperatively map the environment. Even in situations where the robot and human are performing separately (not within sight), the human is able to see through AR the areas that are unexplored and choose to explore them. Figure 4 shows exemplar results from adding communication of the exploration task state. In Fig. 4a, the robot and teammate enter the building together. We can see that in Fig. 4b, the human chooses to explore a large, unknown region of the environment.

Information gain measurements using this communication strategy are presented in Figs. 6d-f across the same three building environments used in the first experiment. We observe that the human's contribution to the overall information gain appears similar, but lesser, than the other communication strategies. We believe this is due to the human teammate making use of the knowledge of exact location of unexplored regions to "fill in the gaps" in the robot's exploration. For example, by carefully mapping small, LIDAR-shadowed areas that the robot might have missed.

D. Communicating Future Actions Enables Multi-Agent Cooperative Performance

For the third experiment, the strategy is to communicate the robot's evaluation of future plans, in terms of exploration frontiers and possible goal locations, as described in Sec. III-C. This information is presented to the human in addition to the information from the previous two experiments.

The human teammate is able to exploit this information for enhanced cooperative performance, as depicted in Fig. 5. The human and robot after entering a building (Fig. 5a). The human is sees the robot's plan to visit the upper goal position to explore the two large frontiers there. The human teammate chooses to explore the lower direction, even through the frontier is smaller (Fig.5b).

Figures 6g-i show the information gain for this strategy. Even though this is a significant amount of information presented to the human via AR, the benefits outweigh the potential costs of cognitive load. The human teammate is able to contribute much more to the overall exploration task than in the previous two experiments. Indeed, in the second and third environments (Fig. 6i) the human teammate is able to map more than the robot.

V. Discussion, Limitations, and Future Work

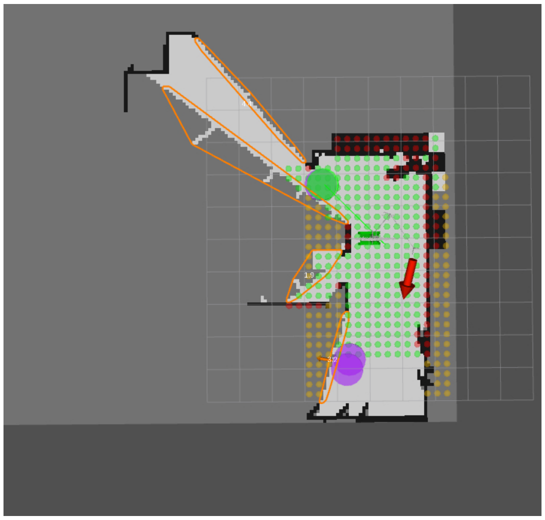
For the task of cooperative mapping, ideally the robot-human team maps completely separate areas. Although this is not feasible in all situations, for example due to environmental topology, minimizing overlap of mapped areas is essential for better team performance.

We observe that the amount of overlap in explored areas by the AR-HMD user and the robot either stays consistent or decreases when the user is given additional information about the robot's understanding of the world (Table I). While this evidence is preliminary, as noted in Sec. IV-D, we believe that this represents the human teammate establishing a mental model of the robot. We believe that the use of augmented reality in these situations helps the user avoid repeating work.

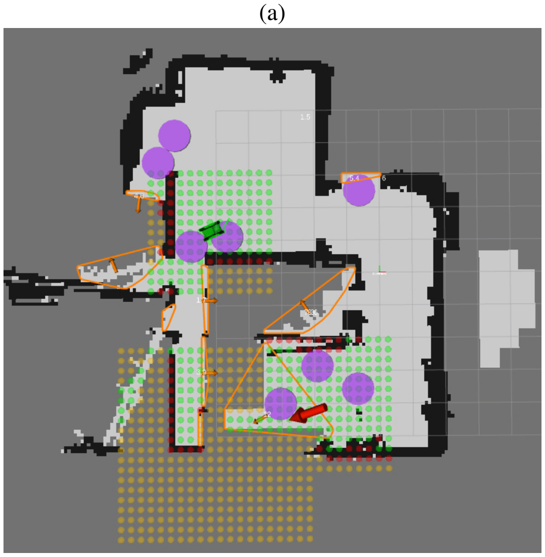
Strategy	**Env 1**	**Env 2**	**Env 3**
Robot Intent	0.51	0.75	0.44
Task State	0.47	0.48	0.40
Future Plans	0.47	0.42	0.44

TABLE I: Exploration overlap - portion of total area that was explored by both teammates.

As noted in Sec. IV-C, the addition of state information may introduce an unintended effect of diminishing the quan-



(a)



(b)

Fig. 5: Time-series results from communicating the robot's future plans as visualized in Rviz. In (a), the human (red arrow) and robot (green rectangle) begin exploring the environment. In addition to the information displayed in Fig. 4, the robot identifies exploration frontiers (orange polygons) and possible goal positions (large purple circles) and selects a goal position (large green circle). In (b), the human has moved to the lower frontier, while the robot has begun exploring the upper frontiers.

tity of information collected by the human teammate. We believe this is due to the human using the state information to more thoroughly uncover even small unexplored regions, leaving the robot to map larger areas.

The main limitation of this work is that the results presented here seek to demonstrate a technological approach and are clearly limited in sample size. They are intended to present the communication strategies from Sec. III, implemented in a system using the enabling technologies from Sec. II, and to encourage discussion and future work. We believe full human studies are warranted for future work.

Additional future work includes examination of other communication configurations, e.g., along both axis of Fig. 1 including deeply exploring methods of communicating more information from the human to the robot to allow the robot to better predict the human and improve robot decision making, experimentation in more challenging and complex field environments, and examination of factors such as diminishing returns for information communication via AR such as cognitive load.

VI. Conclusion

To enable the treatment of humans and robots as peer teammates in real-world field environments, we have examined the use of communication via augmented reality to influence the behavior of a human teammate in a human-robot team task: cooperative exploration of an unstructured and uninstrumented environment. We have presented an approach that communicates human exploration information from the AR-HMD to the robot teammate, and explored the effects of three levels of information communication from the robot to the human on the team's information gain performance: 1) communicating the robot's current plan, 2) communicating the task state, and 3) communicating future actions. Our preliminary results show that it is indeed possible to shape human-robot team performance through communication via AR in this manner. We believe that this is an important step towards determining how AR can be used to shape human behavior in cooperative teams in field environments, which demonstrates that there are many opportunities for future work (Sec. V) to explore directions of great potential.

/ss

References

[1] M. A. Goodrich, A. C. Schultz *et al.*, "Human–robot interaction: a survey," *Foundations and Trends in Human–Computer Interaction*, vol. 1, no. 3, pp. 203–275, 2008.

[2] S. A. Mostafa, M. S. Ahmad, and A. Mustapha, "Adjustable autonomy: a systematic literature review," *Artificial Intelligence Review*, pp. 1–38, 2017.

[3] L. Lin and M. A. Goodrich, "Sliding autonomy for uav path-planning: Adding new dimensions to autonomy management," in *Proceedings of the 2015 International Conference on Autonomous Agents and Multiagent Systems*. International Foundation for Autonomous Agents and Multiagent Systems, 2015, pp. 1615–1624.

[4] J. R. Hoare and L. E. Parker, "Using on-line conditional random fields to determine human intent for peer-to-peer human robot teaming," in *Intelligent Robots and Systems (IROS), 2010 IEEE/RSJ International Conference on*. IEEE, 2010, pp. 4914–4921.

[5] M. Anderson and N. Papanikolopoulos, "Implicit cooperation strategies for multi-robot search of unknown areas," *Journal of Intelligent and Robotic Systems*, vol. 53, no. 4, pp. 381–397, 2008.

[6] O. Feinerman, A. Korman, Z. Lotker, and J.-S. Sereni, "Collaborative search on the plane without communication," in *Proceedings of the 2012 ACM symposium on Principles of distributed computing*. ACM, 2012, pp. 77–86.

[7] M. Otte, M. Kuhlman, and D. Sofge, "Competitive target search with multi-agent teams: symmetric and asymmetric communication constraints," *Autonomous Robots*, vol. 42, no. 6, pp. 1207–1230, 2018.

[8] M. R. Endsley, "Toward a theory of situation awareness in dynamic systems," in *Situational Awareness*. Routledge, 2017, pp. 9–42.

[9] A. R. Selkowitz, S. G. Lakhmani, and J. Y. Chen, "Using agent transparency to support situation awareness of the autonomous squad member," *Cognitive Systems Research*, vol. 46, pp. 13–25, 2017.

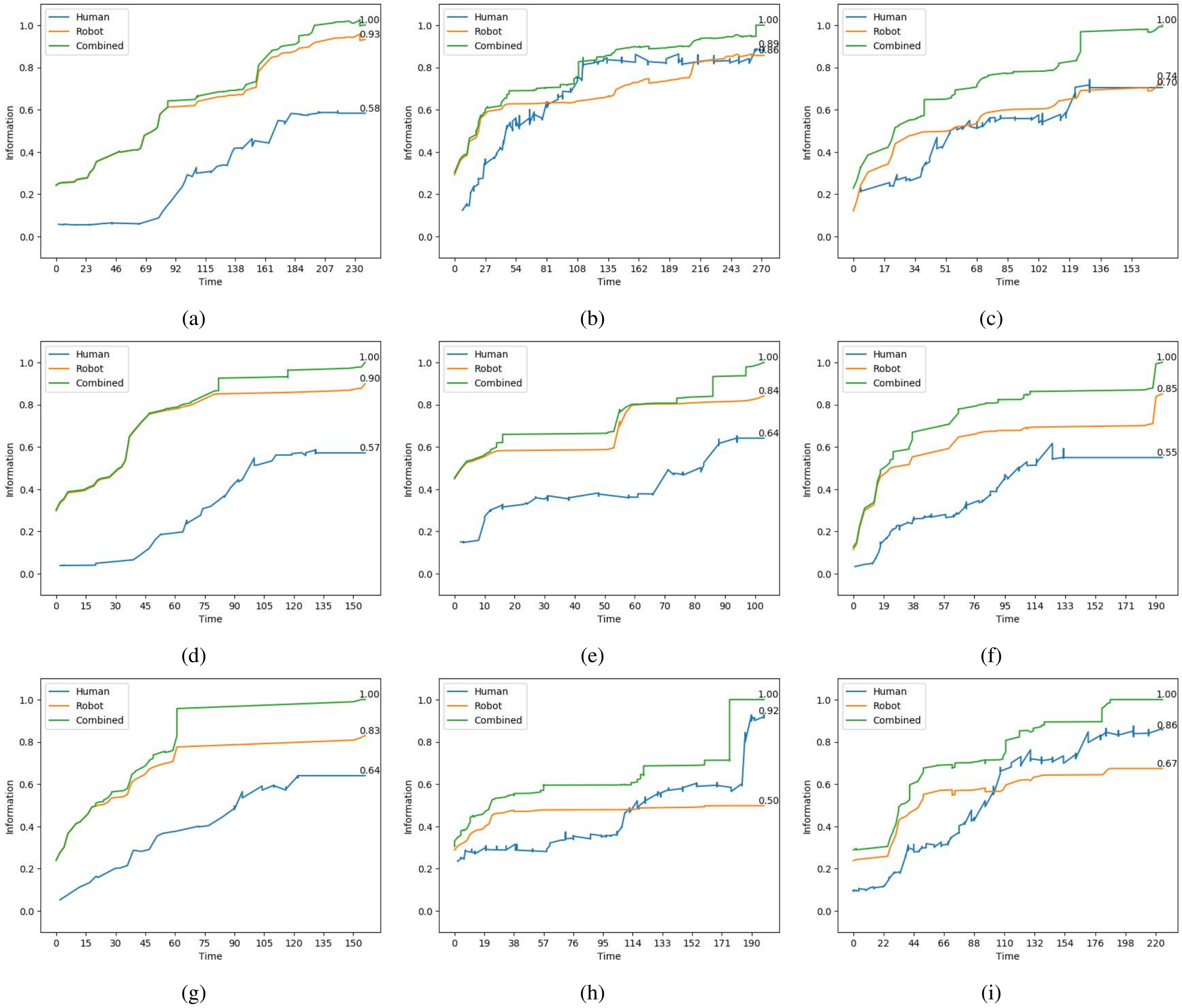


Fig. 6: Information gain results in three different environments (columns $\{(a),(d),(g)\}$, $\{(b),(e),(h)\}$, and $\{(c),(f),(i)\}$) for three different strategies (rows): communicating the robots current plan (a)-(c), communicating the exploration state (d)-(f), and communicating the robot's full world model (g)-(i). Note combined information gain is not the sum of human and robot information gain due to overlaps in exploration.

[10] S. Park, Y. Oh, and D. Hong, "Disaster response and recovery from the perspective of robotics," *International Journal of Precision Engineering and Manufacturing*, vol. 18, no. 10, pp. 1475–1482, 2017.

[11] R. R. Murphy, *Disaster robotics*. MIT press, 2014.

[12] T. Kollar and N. Roy, "Efficient optimization of information-theoretic exploration in slam." in *AAAI*, vol. 8, 2008, pp. 1369–1375.

[13] B. J. Julian, S. Karaman, and D. Rus, "On mutual information-based control of range sensing robots for mapping applications," in *IEEE International Conference on Intelligent Robots and Systems*, 2013.

[14] B. Charrow, S. Liu, V. Kumar, and N. Michael, "Information-theoretic mapping using Cauchy-Schwarz quadratic mutual information," in *IEEE International Conference on Robotics and Automation*, 2015.

[15] W. Burgard, M. Moors, C. Stachniss, and F. E. Schneider, "Coordinated multi-robot exploration," *IEEE Transactions on robotics*, vol. 21, no. 3, pp. 376–386, 2005.

[16] M. Corah and N. Michael, "Distributed matroid-constrained submodular maximization for multi-robot exploration: theory and practice," *Autonomous Robots*, Jul 2018. [Online]. Available: https://doi.org/10.1007/s10514-018-9778-6

[17] A. J. Smith and G. A. Hollinger, "Distributed inference-based multi-robot exploration," *Autonomous Robots*, pp. 1–18, 2018.

[18] N. Fung, C. Nieto-Granda, J. Gregory, and J. G. Rogers, "Autonomous exploration using an information gain metric," U.S Army Research Laboratory ARL-TR-7638, , March 2016.

[19] C. Reardon, K. Lee, and J. Fink, "Come see this! augmented reality to enable human-robot cooperative search," in *Proceedings of the 2018 IEEE Symposium on Safety, Security, and Rescue Robotics*, 2018.

[20] A. Segal, D. Haehnel, and S. Thrun, "Generalized-icp." in *Robotics: science and systems*, vol. 2, no. 4, 2009, p. 435.

[21] A. J. B. Trevor, J. G. Rogers, and H. I. Christensen, "Omnimapper: A modular multimodal mapping framework," in *2014 IEEE International Conference on Robotics and Automation (ICRA)*, May 2014, pp. 1983–1990.

[22] M. Likhachev, "Search-Based Planning Library," https://github.com/sbpl/sbpl. [Online]. Available: https://github.com/sbpl/sbpl

[23] B. Yamauchi, "A frontier-based approach for autonomous exploration," in *Computational Intelligence in Robotics and Automation, 1997. CIRA'97., Proceedings., 1997 IEEE International Symposium on*. IEEE, 1997, pp. 146–151.

[24] J. Gregory, J. Fink, E. Stump, J. Twigg, J. Rogers, D. Baran, N. Fung, and S. Young, "Application of multi-robot systems to disaster-relief scenarios with limited communication," in *Field and Service Robotics*. Springer, 2016, pp. 639–653.