Collaborative Human-Robot Exploration via Implicit Coordination

Yves Georgy Daoud, Kshitij Goel, Nathan Michael, and Wennie Tabib

Abstract—This paper develops a methodology for collaborative human-robot exploration that leverages implicit coordination. Most autonomous single- and multi-robot exploration systems require a remote operator to provide explicit guidance to the robotic team. Few works consider how to embed the human partner alongside robots to provide guidance in the field. A remaining challenge for collaborative human-robot exploration is efficient communication of goals from the human to the robot. In this paper we develop a methodology that implicitly communicates a region of interest from a helmet-mounted depth camera on the human’s head to the robot and an information gain-based exploration objective that biases motion planning within the viewpoint provided by the human. The result is an aerial system that safely accesses regions of interest that may not be immediately viewable or reachable by the human. The approach is evaluated in simulation and with hardware experiments in a motion capture arena. Videos of the simulation and hardware experiments are available at: https://youtu.be/7jgkBpVF1oE.

I. INTRODUCTION

State-of-the-art exploration methodologies leverage the human as an operator outside of the exploration environment instead of directly engaging them side-by-side with robots [1, 2, 3]. Modeling the human as a collaborator instead of an operator in a shared workspace for exploration enables more efficient distributed exploration and useful emergent robot behaviors [4]. In this work, a collaborative human-robot exploration system is developed to explore 3D unstructured environments (Fig. 1a) by communicating the field of view (FoV) of the human to the robot (Fig. 1b) and having the robot use this region of interest (ROI) to bias motion plans to acquire views of areas occluded to the human (Fig. 1c).

Explicit robot tasking is impractical [5] during time-sensitive human-robot collaborative exploration (e.g. cave search and rescue) if humans must reduce their operational tempo [6, 7, 8], so implicit communication of spatial goals is imperative. State-of-the-art exploration objectives reduce environmental uncertainty without providing the flexibility to prioritize ROIs. To address these gaps in the state of the art, this work presents a collaborative human-robot exploration system that: (1) leverages implicit communication to spatially task an aerial system to regions occluded to the human, and (2) develops an information-gain based objective function inspired by the active object reconstruction literature [9] to bias motion planning within the ROI specified by the human. The approach is evaluated with real-time simulations and real-world hardware experiments in a motion capture arena.

II. RELATED WORK

This work lies at the intersection of two key areas: implicit coordination for collaborative human-robot exploration and motion planning objectives for active mapping. In this section we review and contrast related works with the method detailed in this paper.

Few prior works study implicit coordination for collaborative human-robot exploration. Govindarajan et al. [4] achieve coordination through a distributed strategy that assigns robots to homotopy classes that are complementary to the ones being traversed by the human. It is assumed that a blueprint of the environment is available to identify homotopy classes before operation. In contrast, the proposed approach does not assume prior information on the environment layout. A motion primitive-based planner is leveraged to maximize information gain, which takes the human’s view into account, and drives the robot to explore regions occluded to the human; therefore, prior environment knowledge is not required.
Within the context of multitasking, implicit communication has been used to augment human situational awareness via a robotic system. Bentz et al. [10] leverage head tracking while a human performs an arbitrary number of complex tasks and fit the data to a visual interest function. An aerial robot uses the visual interest function to provide camera views that augment the human’s situational awareness. This methodology does not directly translate to the exploration context because the visual interest function, which effectively rates the utility of a viewpoint, is difficult to specify before or during exploration. Instead, the proposed approach uses the notion of potential information gain over a discrete set of candidate viewpoints to drive the robot towards the ROI.

Reardon et al. [11] leverage augmented reality to share information between a robot and human cooperatively exploring in the field. The goal is to influence the behavior of the human teammate in the human-robot cooperative exploration task by sharing information about the robot’s current plan, the task state, and communicating future actions. In contrast, the proposed approach develops a methodology to influence the robot’s behavior depending on actions taken by the human. This implicit coordination is desirable in applications like search and rescue where the robot is expected to adapt to the human’s operational tempo.

Many motion planning objectives have been proposed for active mapping. Frontier-based objectives utilize the distance to the boundary between unknown and known space to drive the robot’s exploration [12]. For multi-agent operation, prioritization between frontiers is utilized to assign agents towards complementary regions of the environment [13]. However, deployments of this idea and its variants have been limited to multiple robots [14, 2], with the human largely supplying spatial goals explicitly when desired [15]. Further, information-theoretic objectives utilize the expected change in the entropy of the map due to candidate sensor measurements to drive viewpoint selection in both 2D [16, 17] and 3D environments [18]. While real-world operation has been shown using single [19] and multiple aerial robots [20], these techniques have not been leveraged in collaborative human-robot exploration. A key capability missing in these objectives is the ability to prioritize spatial ROIs. Towards imposing such spatial constraints, volumetric next-best-view (NBV) selection methods have been proposed for the active object reconstruction problem where the viewpoint is generated to focus on high-fidelity reconstruction of a single object [21, 22]. Delmerico et al. [9] propose several variants of information gain objectives that are either counting-based [21], probabilistic [22], or a combination. However, a method to apply these objectives in the collaborative human-robot exploration system is lacking in the literature. To this end, this work proposes and evaluates an Occulsion-Aware Volumetric Information (OAVI) objective that extends the work of Delmerico et al. [9] to the collaborative human-robot exploration problem. We further contrast it to ROI-constrained Cauchy-Schwarz Quadratic Mutual Information (ROI-CSQMI), an extension of [18] developed in this work, which applies the human’s FoV as a spatial constraint.

### III. METHODOLOGY

This section details the collaborative human-robot exploration method. The human and robot incrementally build a shared map of the environment using range measurements, while the robot uses the occupancy, ROI, and distance information within the shared map for motion planning. We first describe the shared map representation.

#### A. Shared Map Representation

The shared map is modeled as a global 3D occupancy grid (OG) map, \( m = \{m_1, ..., m_{|m|}\} \). Each cell \( m_i \) contains a tuple of three scalar features: (1) the probability of occupancy \( o_i \), (2) a boolean indicating if the cell is in the ROI \( b_i \), and (3) the distance of the cell from the closest obstacle \( d_i \). Each cell \( m_i \) is initially presumed unknown \((o_i = 0.5)\), considered outside the ROI \((b_i = 0)\), and assumed to be at an infinite distance from the closest obstacle \((d_i \rightarrow \infty)\). The range measurements at time \( t \) are denoted by \( z_i^t \) for the human and \( z_r^t \) for the robot. It is assumed that the global position and orientation of these sensors are perfectly known.

For the cells within the FoVs of \( z_h^t \) and \( z_r^t \), the probability of occupancy \( o_i \) is updated using the standard log-odds update [23]. However, the ROI values \( b_i \) are only set to 1 within the FoV of \( z_h^t \). The FoV is mathematically modeled using the fusion of two triangles in 2D and two tetrahedrons in 3D built from the sensor’s intrinsic matrix (see Fig. 2a).

A subset of cells corresponding to inliers of the FoV are shown in Fig. 2b. This subset is extracted via inlier queries with respect to the tetrahedrons on the centers of all cells in the shared map. The distance values \( d_i \) are updated for the cells raycasted by both \( z_h^t \) and \( z_r^t \) with the Euclidean distance from the nearest occupied cell. We utilize the approximation by Delmerico et al. [9] that extends the rays behind a hit cell, \( m_{\text{hit}} \), and populates the distance value at the current time, \( d_i^t \), for the remaining raycasted cells:

\[
d_i^t = \begin{cases} 
\|f(m_{\text{hit}}) - f(m_i)\|_2, & \text{if } \|f(m_{\text{hit}}) - f(m_i)\|_2 < d_i^{t-1} \\
\exp(-1), & \text{otherwise}
\end{cases}
\]

where \( d_i^{t-1} \) is the previously stored distance in cell \( m_i \) and \( f : \mathbb{R}_+ \rightarrow \mathbb{R}^n \) is a function that converts a cell index to the cell position in the world frame. \( n = 2 \) or \( n = 3 \) depending on the dimensionality of the map representation.

![Fig. 2: (a) The human’s field of view (FoV) is shown in red and used to determine which (b) cells in the global occupancy map are within the ROI (shown in green).](image-url)
After obtaining the first observation from the human and updating the shared map, the robot iteratively performs a two-step process: updating the map and selecting the next best action. The rate of this process is specified by the user prior to operation. The space of candidate actions used for action selection is generated using a library of forward-arc motion primitives for a depth camera as presented in [19]. The best primitive is chosen by maximizing the information gain over this discrete action space, which is computed at the end viewpoint of each motion primitive. We contribute one information gain objective function, OA VI, and contrast to the proposed information-gain objective function, OA VI, which prioritizes regions within the FoV of the human and robot during exploration by placing higher weight on views that intersect the ROI.

However, there are two drawbacks to this modification: (1) the objective weights all cells within the occluded region equally, as opposed to the regions closer to the obstacle within the human’s FoV, and (2) once the robot enters the ROI during exploration, it is unlikely that it will exit it. The OA VI objective, presented next, alleviates these drawbacks.

### C. Occlusion-Aware Volumetric Information (OAVI)

The proposed information-gain objective function, OAVI, is inspired by [9] and modifies the uncertainty-aware, \(I_{UA}\), the ROI, \(I_{ROI}\), and the proximity-aware, \(I_{PA}\) metrics.

The uncertainty-aware metric \(I_{UA}\) measures the uncertainty of the cell and accounts for potential occlusions:

\[
I_{UA}(m_i) = H(m_i)P_V(m_i).
\]

\(H(m_i)\) is Shannon’s entropy [24] of cell \(m_i\), and \(P_V(m_i)\) is the likelihood that the cell is visible from the current sensor pose. The result is shown in Fig. 4a for the 2D map in Fig. 3b and illustrates high weights in the unknown space.

The ROI metric, \(I_{ROI}\), biases the objective values towards the ROI. We employ the information stored in the shared map (Section III-A) to mark the contribution of cells in the ROI towards \(I_{ROI}\) as 1. For the other regions of the map, the contribution is set to a user-specified value, \(\alpha_{ROI} < 1\):

\[
I_{ROI}(m_i) = \begin{cases} 
1, & \text{if } b_i = 1 \\
\alpha_{ROI}, & \text{otherwise}
\end{cases}
\]

Intuitively, \(\alpha_{ROI}\) controls the weight given to the unknown regions of the environment outside the ROI. A non-zero \(\alpha_{ROI}\) enables the robot to explore unknown regions after...
prioritizing occluded regions within the ROI. This metric is shown in Fig. 4b with $\alpha_{ROI} = 0.15$ for the 2D map in Fig. 3b.

The same modification is applied for the proximity-aware metric, $I_{PA}$, which utilizes the distance values, $d_i$, in the cells:

$$I_{PA}(m_i) = \left \{ \begin{array}{ll} d_{\text{max}} - d_i, & \text{if } \alpha_i = 0.5 \text{ and } d_i \leq d_{\text{max}} \\ \alpha_{PA}, & \text{otherwise} \end{array} \right. \quad (5)$$

where $d_{\text{max}}$ is the max sensor range, $d_i$ is the distance from cell $m_i$ to the closest raytraced occupied cell, and $\alpha_{PA} \in [0, 1)$ is a tunable parameter. This modification produces a gradient that places higher weights on cells close to an observed surface (e.g. see Fig. 4c where $\alpha_{PA} = 0.10$).

The final information gain $I_{OAVI}$ is defined as the cumulative product of each metric over the raycasted cells $\hat{m}$ corresponding to the robot measurement at the viewpoint $z_i^r$:

$$I_{OAVI}(\hat{m}; z_i^r) = \sum_{i \in |(\hat{m})|} I_{OAVI}(\hat{m}_i) = \sum_{i \in |(\hat{m})|} I_{UA}(\hat{m}_i) I_{ROI}(\hat{m}_i) I_{PA}(\hat{m}_i). \quad (6)$$

Figure 4d illustrates the heatmap corresponding to $I_{OAVI}(\hat{m}; z_i^r)$. Note the gradient behind the obstacle in OAVI, which has the effect of weighting the viewpoints that observe occluded regions more heavily, and contrast this with the uniform weighting of ROI-CSQMI in Fig. 3d.

IV. EXPERIMENTAL DESIGN AND RESULTS

The approach is evaluated in simulation and with real-world hardware experiments. The experiment begins when the human transmits the pose of their helmet-mounted range sensor with the corresponding pointcloud to the robot partner. Only one instance of these pose and pointcloud pairs is transmitted for both simulation and hardware experiments. The proposed methodology may allow for multiple pose and pointcloud pairs, but this is left as future work. When the robot receives data from the human, exploration begins.

The OAVI approach is compared against the ROI-CSQMI and CSQMI approaches. Two quantitative and one qualitative measure are used to evaluate performance. The two quantitative evaluations measure the entropy of the map and ROI over time. The qualitative evaluation plots the evolution of the robot’s trajectory over time.

A. Simulation Experiments

Simulations in four environments (Fig. 5) are conducted to evaluate the approaches developed in this work against the baseline approach. The simulation environments consist of a single wall, two walls, multiple obstacles, and the cave environment from Fig. 1 with the same human-robot placement. In each environment the goal is for the robot to obtain views in regions occluded to the human. These environments are selected to highlight the merits and drawbacks of the information gain objectives.

In each environment, the human faces the area of interest. The human’s FoV, which is the FoV of a simulated depth camera on the human’s head, is shown as red lines in Fig. 2a. The robot is placed at a randomly selected location within a $4 \times 4$ m box around the human’s starting position. After the human transmits their pointcloud observation and pose to the robot, the robot updates its onboard map according to Section III-C. Each exploration variant is run for 30 trials per environment for a total of 360 trials over all environments and variants. Exploration is terminated after 10 min resulting in a total of 60 h of simulations.
The entropy of the ROI is plotted over time for each environment in Figs. 5e to 5h and the entropy of the map (including the ROI) is plotted over time in Figs. 5i to 5l. In analyzing the performance of Figs. 5e to 5h one can see that OAVI and ROI-CSQMI decrease the uncertainty of the ROI approximately 3× faster than CSQMI. ROI-CSQMI slightly outperforms OAVI because the mutual information of a view entirely outside of the ROI is zero, which means that the robot will not select actions outside the ROI. In contrast, OAVI tends to drive the robot outside the ROI after sufficient views of the ROI have been acquired. When analyzing the map entropy over time in Figs. 5i to 5l, one can see that the final map entropy of the OAVI approach at 600 s is on average 56% lower than the ROI-CSQMI approach across environments. The baseline CSQMI approach outperforms the other approaches because it selects views that maximize the mutual information between the map and sensor without consideration for the ROI.

From these results, we arrive at the following conclusions: first, the baseline CSQMI approach is not well suited for collaborative human-robot exploration because it does not bias the exploration towards the ROI; second, the ROI-CSQMI approach is ideal for a leader-follower exploration strategy because it selects motion plans that are restricted within the ROI; and third, the OAVI approach is ideal for a collaborative framework where the robot biases views within the ROI first and then selects observations outside the ROI.

Figure 6 plots the top-down views of the trajectories taken by the robot for the three approaches in the two walls environment (shown in Fig. 5b). The evolution of the trajectory for \( t = \{30, \ldots, 60\} \) s in Fig. 6 demonstrates that OAVI first explores the occluded region closest to the human observer and then proceeds to the second obstacle after the robot has updated its distance field. In comparison, ROI-CSQMI does not incorporate a measure of the distance to obstacles so it selects actions that maximize the mutual information between the potential observation and ROI, while CSQMI explores areas outside of the human’s ROI for the first 60 s because it does not have a notion of the human’s ROI.
B. Hardware Experiments

Experiments are run inside a motion capture arena to validate the proposed approach against the baselines in the real-world. The human is equipped with a helmet-mounted Intel RealSense D455 depth camera (see Fig. 7). The robot, a 2.5 kg quadrotor, carries a forward-facing D455 and two onboard computers: an NVIDIA TX2 running state estimation and control, and an Intel i7 NUC 11 with 32GB of RAM, which runs mapping, planning, and collision avoidance.

The set of parameters used in the hardware experiments (see Fig. 8) are listed in Table I. Each approach is run once starting from the same initial robot pose and a fixed helmet orientation for a total time of 2 min.

Fig. 7: (Left) Aerial robot and (Right) helmet for the human partner used in the hardware experiments.

Fig. 8: A human-robot team explores an environment inside a motion capture arena, with an obstacle in front the human requiring the robot to provide complementary views.

Fig. 9: ROI and map entropy as a function of time for the three approaches. The baseline CSQMI approach reduces the total uncertainty in the environment fastest Fig. 9b. ROI-CSQMI explores the ROI twice as fast as OAVI, and 4× as fast as CSQMI (see Fig. 9a) but does not select actions outside of the ROI once it reaches the ROI. This behavior yields the blue plateau in the map at $t = 50\, \text{s}$. In contrast, OAVI explores the rest of the unknown environment as shown in the final map (Fig. 10), reducing the map entropy by 75% more than ROI-CSQMI.

Table II: Planning times onboard the robot’s computer during hardware experiments show the computational-efficiency of the proposed approach.

![Table II: Planning times onboard the robot’s computer during hardware experiments show the computational-efficiency of the proposed approach.](image)
To demonstrate computational-efficiency of the proposed approach, we record the planning times taken by the action generation, scoring, and best primitive selection modules onboard the robot’s computer. The results reported in Table II show close planning times between the three approaches, allowing our OAVI planner to run at up 15 Hz.

V. CONCLUSION

This paper presented a methodology for collaborative human-robot exploration with implicit coordination. The approach developed in this work, OAVI, is an information-gain objective function inspired by active reconstruction techniques. The proposed approach was compared against an information-theoretic exploration baseline, CSQMI, and an extension to this baseline, ROI-CSQMI, which applies a spatial constraint to bias actions within the human’s FoV.

Comparing these approaches in simulation and hardware yields the following conclusions: (1) the baseline CSQMI approach is not well-suited to the collaboration paradigm detailed in this paper because it has no notion of the human’s ROI and cannot bias motion plans to reduce uncertainty towards the human’s FoV; (2) the ROI-CSQMI approach is ideal for a leader-follower exploration strategy because it selects motion plans that are restricted within the ROI; and (3) the OAVI approach is ideal for the collaborative human-robot exploration paradigm outlined in this paper because it causes the robot to select views within the ROI first and then explore outside the ROI when a sufficient number of views within the ROI have been collected.

In future work, we aim to deploy the exploration system for longer durations and with a moving human collaborator in outdoor, field environments. Further, we will relax assumptions on perfect knowledge of human-robot poses and their relative transforms in the world frame.

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