Improving efficiency of human-robot collaborative search in unknown environments using human behavior estimation and bidirectional communication

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Abstract

この研究の目的は、自律移動ロボットによる物体探索手法の効率を向上させることである。先行研究で使用された過去の人間の行動の推定と未来の人間の行動の予測手法を拡張し、双方向通信に焦点を当てた。特に、人間がロボットの過去および未来の探索行動をリクエストできるようにすることで、物体探索タスクにおいて重複した探索を避ける手法を提案し、その有効性をシミュレーションにて検証した。

The goal of this research is to increase the efficiency of the object search method by an autonomous mobile robot. This research is an extension of its predecessor, which used methods of estimating past human behavior, and predicting future human behavior. This research focuses on bidirectional communication, where the human can request the robot ’s past and future search behavior. In object search tasks, there is a tendency for human subjects to search an area that the robot has already searched, as there is no way for the human to recognize a searched area other than by direct observation. To avoid redundant searches, we implement the bidirectional communication method to the previous research ’s methods and verify its effectiveness in simulation.

Contents

1 Introduction

1.1 Background and Objective

The rapid advancements in robotics and artificial intelligence have propelled the integration of robots into various aspects of human life. One area that holds significant promise is the collaborative exploration of unknown environments, where humans and robots work together to efficiently search and gather information. Unknown environments pose unique challenges for exploration, including the risk of duplicate searches. Inefficiencies arise when both human and robot agents cover the same areas, leading to wasted resources and time. By addressing these challenges and developing effective communication strategies, mobile robots have the potential to significantly improve the efficiency of search tasks, as well as reducing wasted resources and time in the exploration of unknown environments.

The previous work [1] proposed a method for estimating and predicting human search behavior in unknown environments, as well as sharing information through dialogue in order to improve collaborative search efficiency and to avoid overlapping search locations. However, although duplicated searches were reduced with this method, the human subject had limited knowledge of the robot's search path, and hence some of the duplicated searches were done instead by the human. Therefore, in this study we propose a bidirectional communication method, where both robot and humans may interact with each other to share information in order to avoid overlapping searches and increase the efficiency of collaborative search tasks. Using the proposed methods, we conduct simulation experiments with and without the presence of communication, and verify the effectiveness of the proposed methods in this study.

1.2 Thesis Organization

The organization of this thesis is as follows; Chapter 2 provides an overview of related studies in the domains of object search and collaborative work. In Chapter 3, we provide a detailed exposition of the envisioned collaborative object search methodology. This includes a thorough exploration of the update method for environmental information, the estimation and prediction of human behavior during the search, and the subsequent formulation of robot action plans based on this acquired information. Chapter 4 introduces our proposed approach aimed at amplifying the efficiency of the collaborative object search method detailed in Chapter 3 by integrating bidirectional dialogue. Chapter 5 presents a comprehensive discussion of experiments conducted to evaluate collaborative object search scenarios involving both human and robot participants within a simulated environment. Finally, Chapter 6 serves as the conclusion of this study, offering a summary and outlining potential avenues for future research challenges.

2 Related Works

2.1 Object Search

In a study by Miake et al. [2], a robotic viewpoint planning method is proposed for maximizing unknown regions in object search on desks. The study assumes robotic solo object search and does not consider human search actions when conducting object search simultaneously with humans. This research aims to maximize the exploration capabilities of both robots and humans by considering human actions in viewpoint planning for object search. Dieter et al. propose the optimization of environmental exploration by robot teams [3]. By merging map data between approaching robots during exploration, they achieve decentralized exploration efficiency even in environments where all robots cannot be controlled by a network. In the study, it is mentioned that exchanging data between robots about their respective search situations for collaborative exploration between robots and humans is challenging.

2.2 Human-Robot Collaboration

In research on human-robot collaborative work, a study by Luke Burks et al. [4] focused on supporting robot exploration by having humans provide information to the searching robot. The task of the study involves faster detection of the exploration target through the collaboration between a robot chasing a moving exploration target and a human observing the camera images of the exploration environment. Humans can convey information from the camera images through a GUI interface. In a study by Ishii et al. [1], which is the precursor of this research, a human movement estimation and prediction method is proposed to maximize collaborative search efficiency by avoiding duplicate searches. The method proposed by the study produces estimation candidates for areas that the human may have visited, as well as prediction candidates for areas the human subject is likely to visit next. For multiple likely candidates, the robot approaches the human subject to ask predetermined questions to determine the most suitable estimation and prediction candidate. This allows the robot to identify areas that have already been visited by the human subject, and search other unknown areas instead. However, it is noted in the study that duplicate searches are sometimes performed by the human subject.

3 Preliminaries

3.1 Collecting Environmental Information

3.1.1 Map Generation

The generation of a labeled two-dimensional occupancy grid map, referred to as LabelMap, is employed to record the structure of the exploration environment and the exploration status based on GMapping [7]. By classifying point cloud data obtained from range sensors mounted on the robot, GMapping generates a two-dimensional map that represents occupied areas, such as walls and traversable non-occupied areas. LabelMap then applies color labels to the two-dimensional occupancy map generated by GMapping, making otherwise indistinct data into a visualized map that can be easily understood and manipulated. An example of the generated LabelMap is illustrated in Figure 3.1.

Simultaneously with map generation, the detection of frontiers is conducted. Frontiers represent the boundaries between unknown regions and non-occupied areas within the map. Frontiers are commonly utilized in frontier-based exploration strategies [11]. In this study, frontiers are considered as candidate viewpoints for the expansion of known regions, as will be elaborated upon later.

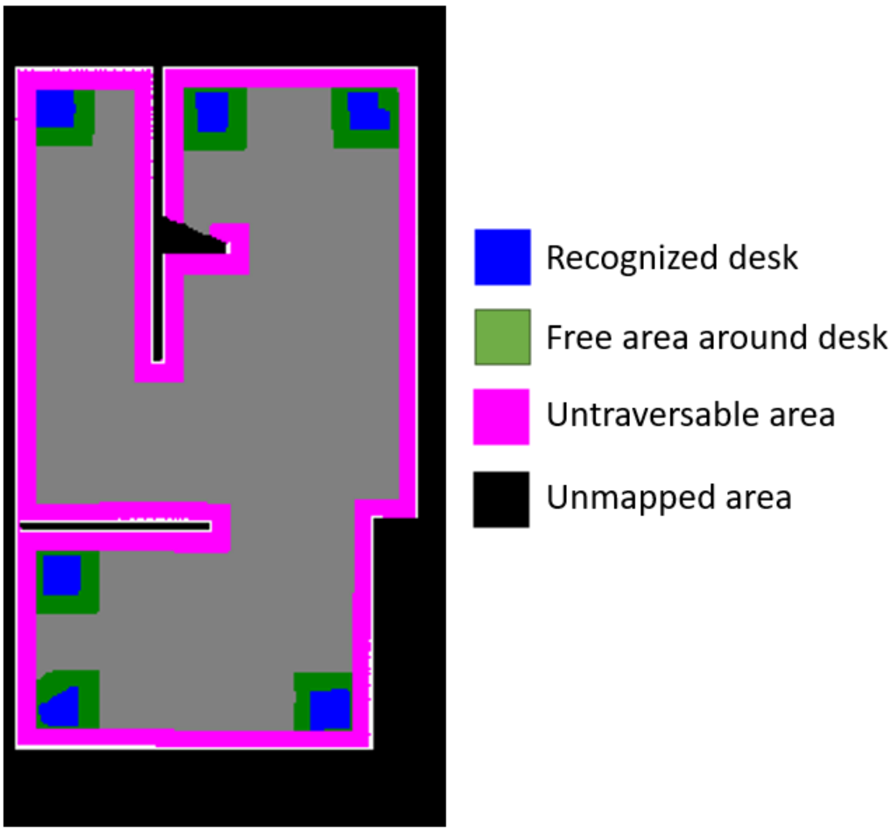

Figure 3.1: An example of a generated LabelMap

3.1.2 Desk Detection

We present a methodology designed to detect desks through the utilization of a 3D voxel map, specifically Octomap [9], to acquire precise information regarding the desk's location throughout the robot's search. In the context of object search within this study, the targeted object is positioned atop a desk. Hence, it becomes imperative for the robot to ascertain the desk's spatial coordinates within the search environment. The three-dimensional voxel map is generated by inputting three-dimensional point cloud data, from the depth camera mounted on the robot's head, into Octomap. Subsequently, a 2D map is derived from the produced 3D voxel map by slicing it according to the height of the desk. The detection of a desk involves identifying an area with a sufficiently large occupied region on the generated 2D map. Figure 3.2 provides an illustrative example of the desk detection process and the consequent labelling of the desk in the LabelMap.

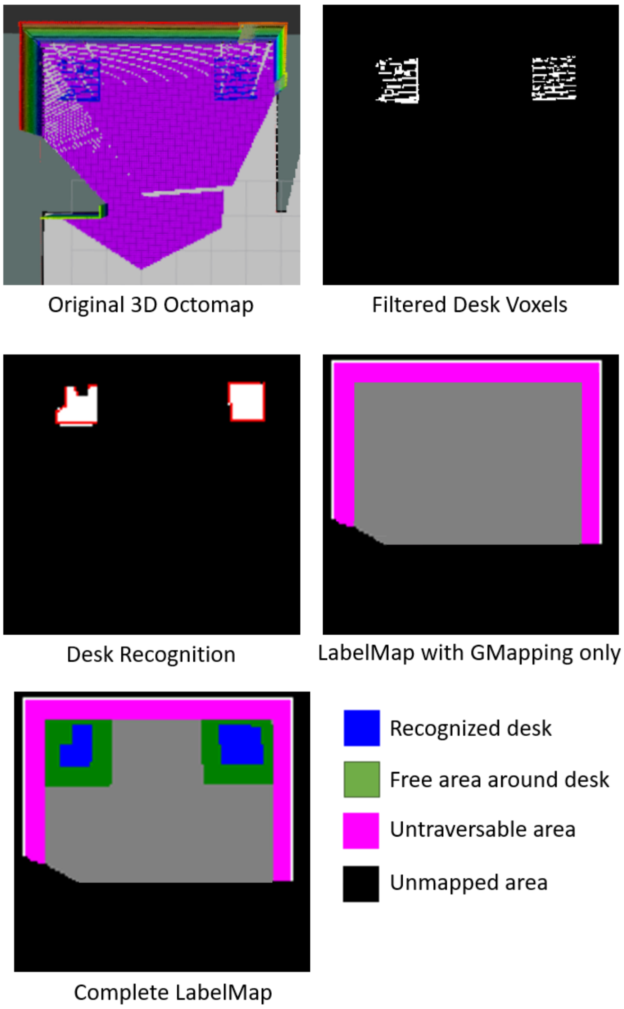

Figure 3.2: Example of Desk Detection

3.2 Fast Marching Method (FMM)

For efficient action planning and estimation and prediction of human actions, it is necessary to calculate the travel time to the detected desk or frontier. The Fast Marching Method (FMM) [10] is used to calculate the travel time. FMM calculates the travel time T from the wave source to each point in space by modeling the motion of waves. By using the position of a desk or a frontier on the map as a wave source, the travel time can be obtained without recalculating the position of a robot or a human in the map. It is also possible to obtain the travel time between desks and frontiers.

The motion of waves can be expressed by an equation known as the Eikonal equation where x is the position, F is the velocity of the wave, and $T(x)$ is the time required for the wave to reach x.

$$1 = F|\nabla T\left(x\right)|$$

In two dimensions, the grid map is used for discretization. Let i, j denote the rows i and columns j of the grid map, corresponding to the real world points $p(x_i, y_j)$. $\Delta x and \Delta y$ denote the grid spacing in the x, y directions. For a discrete two-dimensional space, the Eikonal equation can be rewritten as in equation (3.1).

$$max\left(\frac{T-T_1}{\Delta x},0\right)^2 + max\left(\frac{T-T_2}{\Delta y},0\right)^2 = \frac{1}{F^2} \tag{3.1}$$

$$T = T_{i,j}$$

$$T_1 = min\left(T_{i-1,j}, T_{i+1,j}\right)$$

$$T_2 = min\left(T_{1,j-1}, T_{i,j+1}\right)$$

When $T > T_1$ と $T > T_2$

$$\left(\frac{T-T_1}{\Delta x}\right)^2 + \left(\frac{T-T_2}{\Delta y}\right)^2 = \frac{1}{F^2} \tag{3.2}$$

If $T_2 \geq T > T_1$

$$\left(\frac{T-T_1}{\Delta x}\right) = \frac{1}{F} \tag{3.3}$$

If $T_1 \geq T > T_2$

$$\left(\frac{T-T_2}{\Delta y}\right) = \frac{1}{F} \tag{3.4}$$

The Eikonal equation can be solved iteratively and represented on the grid map. Each individial cell in the gridmap are labeled as follows;

- Unknown: A cell whose value is not yet known (the wave has not yet reached the cell)
- Narrow Band: Cells where the wave will reach in the next iteration. It is assigned a temporary T that can be changed
- Frozen: A cell where the wave has already passed and the T is fixed

The algorithm has three stages: initialization, main loop, and finalization. Each of these stages are described below.

・Initialization

The algorithm begins by setting $T = 0$ in the cells of the wave source. This cell is labeled as Frozen. Subsequently, the adjacent cells that are not yet Frozen are labeled as Narrow Band. For each of these cells, the equation (3.1) is solved and T is calculated.

・Narrow Band

In each iteration, the equation (3.1) is solved for the non-Frozen adjacent cells of Narrow Band cells with smaller T values. The cells are then labeled as Frozen. Narrow Band maintains an ordered list of these cells, arranged in descending order based on their T values.

・Finalization

The algorithm terminates when all cells become Frozen (or when there are no more Narrow Band cells). The resulting grid map contains, for each pixel, the arrival time T from the wave source.

The calculation using FMM needs to be performed every time the map is updated. However, it is resource-intensive to recalculate the FMM from the wave source for each update. Therefore, before finalization, the last Narrow Band is recorded, and for every update, the computation resumes from the last Narrow Band. This significantly reduces unnecessary calculations for cells that have already been computed once.

3.3 Human Movement Estimation and Prediction

3.3.1 Human Movement Estimation

In Section 3.3.1 and Section 3.3.2 , we provide an overview of the work conducted by T. Ishii et al., upon which our current study is built. When observing a human, the robot estimates the search path from the previous to the current human position, considering the path to traverse near a desk due to the search target's placement. The time to move between points varies based on traversed desks. Comparing actual elapsed time and travel time helps estimate the specific desk on the route depending on the combination of desks. In unknown environments with undetected desks, it is impossible to calculate the possible placements of the desks, hence the frontier is introduced as a candidate instead. A route is formed by combining detected desks and the frontier. Calculating travel times, paths close to actual travel times serve as estimation candidates. In the unknown region, where travel time between frontiers cannot be directly calculated, the difference between actual elapsed time and travel time is recorded as time spent. This time spent is determined by the difference between elapsed time and combined travel time in the known region. Additionally, a minimum time spent between frontiers is defined as the minimum travel time through an open unknown region between two frontiers. If this minimum stay time cannot be exceeded, regardless of the unknown region's shape, passage is deemed impossible. In the case of moving through the same unknown region between the same frontiers, the travel time to the same frontier is considered as 0 seconds, hence the shortest stay time is set to 5 seconds instead.

During the generation of candidate routes, we assume that the following conditions are fulfilled throughout the recursive exploration of the visit order list for all desks and frontiers:

- For combinations exclusively involving desks, the search is halted if the difference between the travel time of the combined route and the elapsed time is less than 20% of the elapsed time.
- For combinations including a frontier, the search is concluded if the travel time of the combined route is less than the elapsed time, and the stay time surpasses the shortest stay time.

In cases where the travel time of the list being examined exceeds the elapsed time by more than 20%, the search is terminated. The search is also halted if the list traverses a frontier, and the stay time is less than the minimum stay time.

Due to the dynamic changes in the frontier during map updates, the route estimation is only performed within the expanded area using the time spent as the elapsed time when the known area is expanded.

Figure 3.3 illustrates a historical route estimation example. In this instance, two desks and two frontiers are detected, and are labeled as 1 and 2. The path from the previous human position to the current human position is estimated by combining Desk 1, Desk 2, and two frontiers in this sequence.

If the elapsed time is 10 seconds and the combined path of the two desks takes 12 seconds, no further combinations are calculated, as no additional combinations satisfy the elapsed time condition. In scenarios where the frontier becomes obsolete due to map updates, route estimation is conducted within the expanded area. The potential routes between identified desks in the expanded area are computed, with the currently obsolete frontier serving as the destination for the estimated paths.

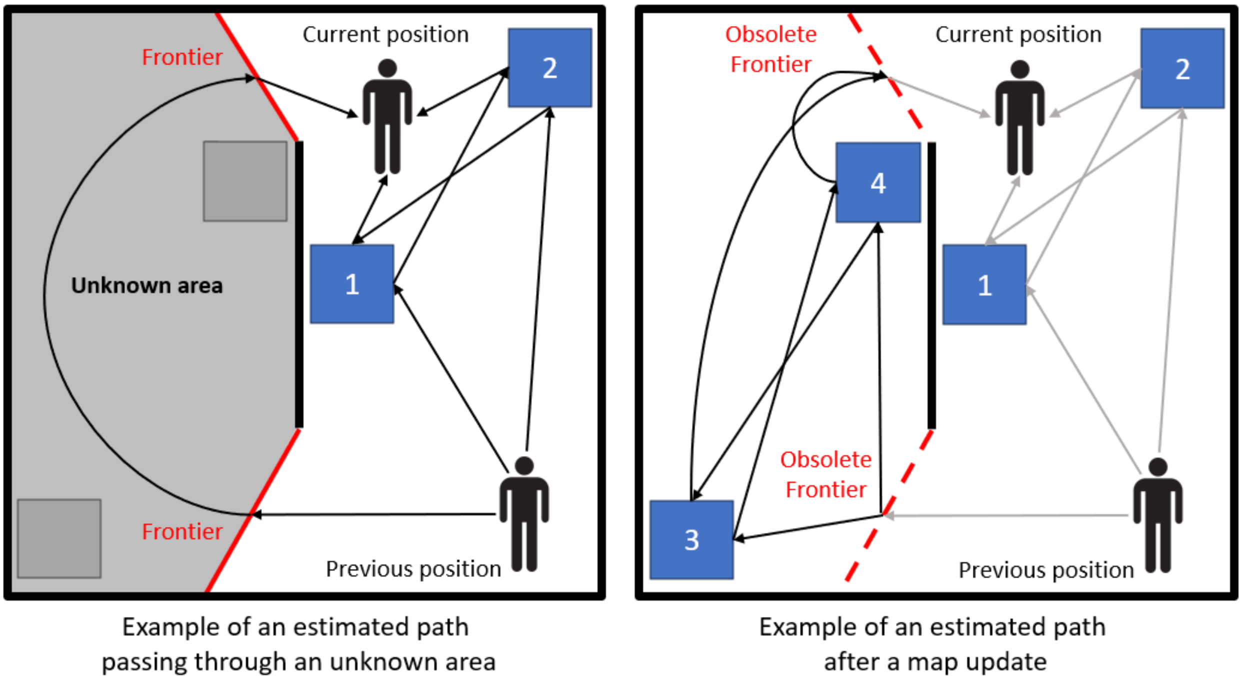

Figure 3.3: Example of the human movement estimation implementation

3.3.2 Human Movement Prediction

We predict the search path that a human will take from the observed human position to a specified future time, referred to as the prediction time, set at 10 seconds. Assuming the human systematically searches unexplored desks, the robot generates a sequence for moving to detected desks and frontiers in order. An illustrative example of action prediction is presented in Figure 3.4. The iterative calculations begin from a state with a total travel time of 0 and continue until the total travel time reaches the prediction time. The procedure involves:

1. Moving to the nearest desk/frontier from the current human position.

2. Adding the travel time to the total travel time.

3. For a desk, incorporate a fixed search time; for a frontier, add time corresponding to the length of the frontier as the time spent in the unknown region.

4. Moving from the desk/frontier to another nearest desk/frontier.

5. Repeating steps 2 to 3 until the total travel time equals the predicted time.

6. The paths generated by this calculation serve as search candidates.

When the time difference in movement between the nearest desk/frontier and the second nearest desk/frontier from the current human position is small, selecting a single prediction candidate becomes challenging. Therefore, if the time difference between moving to the nearest desk/frontier and moving to the second or subsequent desk/frontier is within 3 seconds, multiple prediction candidates are generated. The corresponding second or subsequent desk/frontier is considered as the initial movement point from the current human position for each additional prediction. Calculations are performed sequentially, starting from the second closest desk/frontier, and the generation of additional predictions is terminated when the difference exceeds 3 seconds.

In the case where the robot is unable to observe the human, the last observed human position is used as a basis for updating prediction candidates. This update involves adding the elapsed time from the last observed instance to the current time to the prediction time. Subsequently, the robot recalculates movements from the last human position to the desks/frontiers in sequence. In scenarios with multiple prediction candidates, the robot-human interaction, elaborated upon later, is employed to single out a specific prediction. If the initially selected frontier, based on the last human position, ceases to exist due to map updates, the information from the original prediction candidates is integrated. To synchronize with the most recent environmental data, the nearest desk/frontier to that particular frontier is designated as the starting point. This ensures an update that reflects the outcomes of the interaction.

Figure 3.4 shows an example of human movement prediction. In this example, candidate predictions are generated and numbered according to the travel time predictions, with the nearest path labelled as 0, and the furthest as 7.

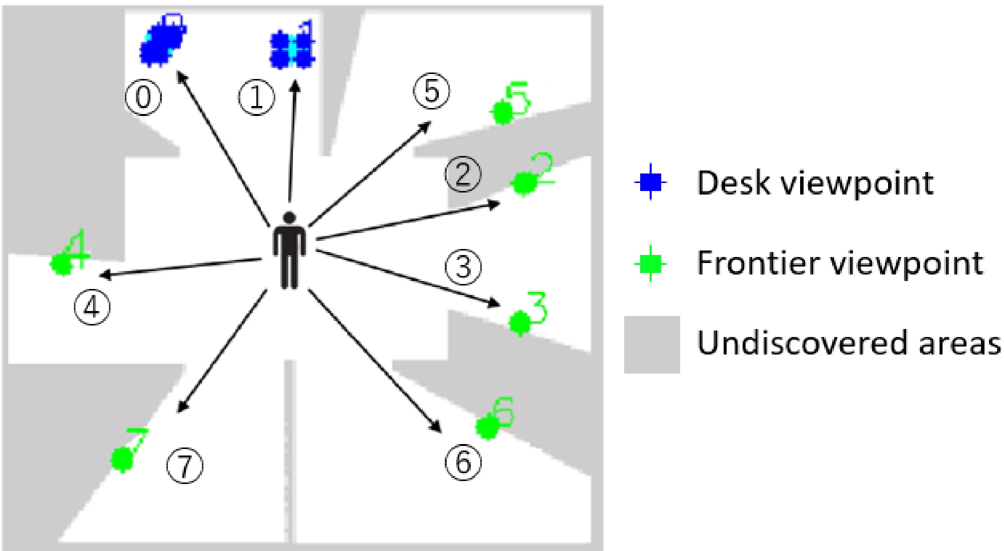

Figure 3.4: Example of human movement prediction

3.4 Action Planning

The robot's action planning is based on a labeled two-dimensional occupancy grid map that incorporates environmental information, estimations, and prediction results. The robot's actions are selected from the following two options:

- Object Exploration : Move to accessible viewpoints that give a clear view of the desk
- Frontier Exploration: Move to the nearest frontier from the robot's position in the map to discover unknown regions

The choice of action is determined by referring to the LabelMap. If there is an unknown region on the detected table that neither the robot nor the human has explored, the Object Exploration is preferred, and the robot will move to get a clear view of the table. Conversely, if there is no unexplored table regions, Frontier Exploration is preferred, and the robot will prioritize expanding the explored area.

The robot's utilizes move_base [12] for its navigation and path planning. For the planning of viewpoints in object exploration, the method by Miake et al. [2] is employed. Miake's work plans the optimal viewpoints for exploring the table based on the distance to move to the table and the reduction in unknown regions on the table. In the planning of the destination of Frontier Exploration, LabelMap visualizes the areas where humans have already moved or are predicted to move, and excludes them from the candidate destinations as these areas are considered non-unknown.

Figure 3.5 illustrates examples of robot's action planning. In cases where there is an unexplored region on a table on the map, Object Exploration is chosen, as shown in the example. Conversely, in cases where the region on the table has no unexplored area and consists only of areas explored by the robot or estimated to be searched by humans, as shown in the example on the right side of the figure, the choice is to expand the known area with Frontier Exploration.

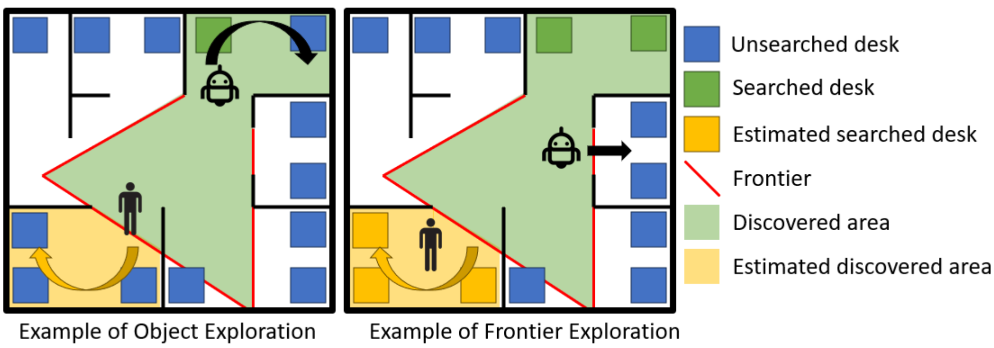

Figure 3.5: Implementation of Object and Frontier Exploration

4 Bidirectional Human-Robot Communication

4.1 Robot-to-Human Inquiries

4.1.1 Initiating an Interaction with the Human

When there are multiple candidates for the estimated or predicted paths of the human subject, reflecting all of them in the LabelMap and excluding them from the robot's candidate exploration destinations may excessively reduce the robot's searchable area, leading to the robot not exploring desks more than necessary. Therefore, we consider eliminating excessive estimation and prediction candidates by engaging in a dialogue through the robot with the human.

The questions are conducted through predetermined question sentences and the robot's pointing gestures. The dialogue is conducted through two types of messages, as shown in Figure 4.1, and the corresponding responses from humans.

When the robot can observe humans, it performs estimation and prediction as described in the first halves of Sections 3.3.1 and 3.3.2, similar to the regular collaborative object search method. If the robot cannot observe humans, it does not update estimation candidates, and continues to use existing candidates until the next time the human is visible. When there are multiple estimation or prediction candidates after human observation, the estimation results are not reflected in the map, and instead a dialogue with humans is initiated. Questions are generated from each estimation and prediction candidate. The robot sends a signaling message and approaches the human subject before asking its question. If the reply from the human subject allow for a unique determination of estimation and prediction candidates, the dialogue concludes, and the resulting estimated paths and predicted paths are reflected in the map. Subsequently, the robot proceeds with its action planning.

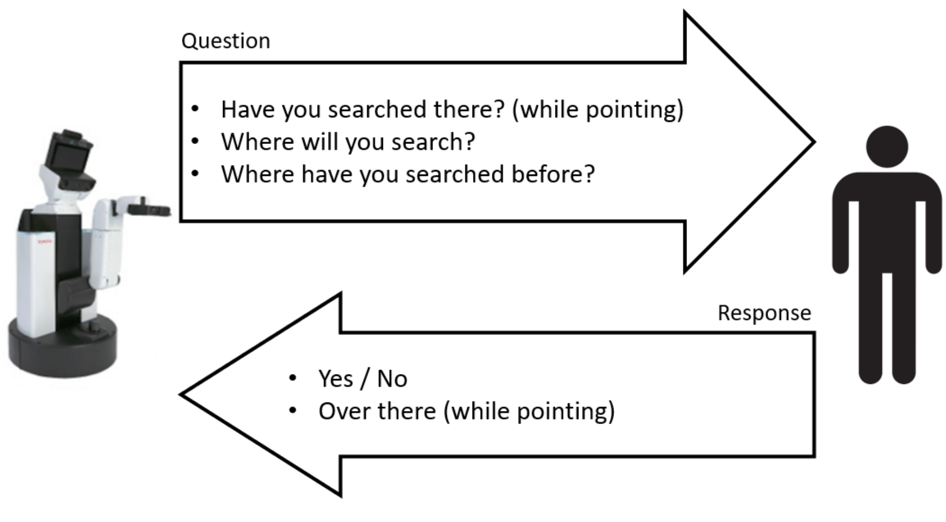

Figure 4.1: Overview of robot-to-human dialogue

4.1.2 Generating Questions

To consolidate multiple estimation candidates obtained through human behavior estimation into a singular result, we utilize questions that are asked to the human. We calculate the deviation of the difference between the elapsed time and travel time for each estimated path. We then compare the value closest to the elapsed time with the second-closest value, and pose the question "Where did you search?" if the difference exceeds a certain threshold. Otherwise, while pointing to the direction of the path closest to the elapsed time, the robot asks "Did you search here?" to the human subject. In the case of the question "Did you search here?" we compute the robot's pointing direction for the question. The robot's pointing direction represents the middle point of the coordinates of desks and frontiers in the estimated path.

Similarly, when multiple prediction candidates are obtained through human behavior prediction, we generate questions to uniquely determine the prediction result. Unlike the question generation for estimation candidates, for prediction candidates, the robot asks the question "Where will you search next?" irrespective of the candidate paths. An example of this implementation is shown in Figure 4.2.

The question messages sent by the robot are played as audio from the simulation's robot. Additionally, they are displayed as text in the simulation's human's point-of-view footage. The robot's pointing direction is conveyed by the simulation's robot moving its arm towards the pointing direction during the simulation, resembling a pointing gesture.

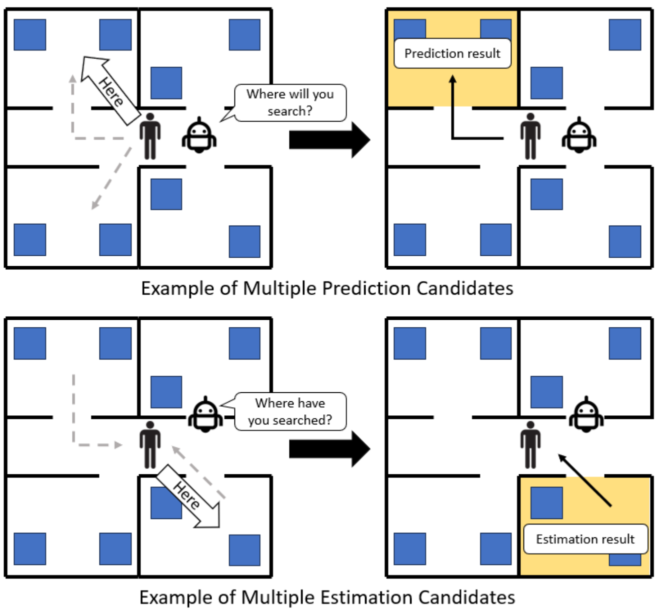

Figure 4.2: Example of the robot-generated questions

4.2 Human-to-Robot Inquiries

In our previous work, although robot-to-human dialogue was proven to be effective in reducing the number of duplicate searches, it was found that some duplicated searches were performed by the human subject, as the human subject had no way to confirm already searched areas unless the robot was always in the human's point of view. Hence, we implement a human-to-robot dialogue, enabling the human to seek clarification from the robot regarding the robot's search history and search plans. The flow of the collaborative object search method with the addition of bidirectional dialogue is shown in Figure 4.3.

To begin an interaction with the robot, the human must first approach the robot at a reasonable distance before calling for its attention. This approach distance is defined as 7.6 meters, which is the outer bounds of public distance in human interpersonal distance[13]. Once within this distance, the robot will respond and move towards the human when its attention is called.

Similar to the robot, the human may present the robot with three questions, "Where did you search?", "Where have you searched?" and, while pointing, "Have you searched there?". The robot will respond with a pointing gesture signifying it's future viewpoint and previous viewpoint respectively for the questions "Where did you search?" and "Where have you searched?", and a "Yes" or "No" response to "Have you searched there?" question.

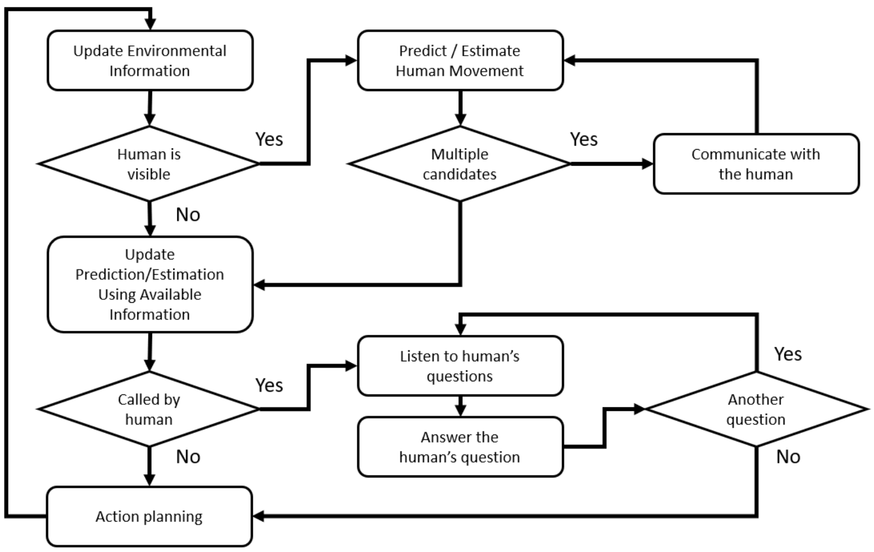

Figure 4.3: Flowchart of the search method with bidirectional communication

4.3 Processing and Receiving Input

4.3.1 Human Input

Throughout the collaborative search task, the human participant engages in the task and communicates with the robot through messages assigned to the controller. The inputs are categorized into two main parts: the left controller is primarily utilized for responding to the robot's queries, while the right controller is mainly used to pose questions to the robot.

In the course of the robot's inquiry within the search process, the human participant utilizes messages assigned to the left controller, as depicted in Figure 4.4. When confronted with the robot's question, "Did you search here?" the participant makes a selection by pressing the corresponding "Yes" or "No" buttons on the left controller. For inquiries like "Where did you search?" and "Where will you search next?" from the robot, the participant directs the controller toward the desired direction, activates the button near the index finger of the controller, and conveys the response with the message "I searched here." The indicated direction is then transmitted to the robot in the simulation.

Alternatively, the human subject can interact with the robot using messages assigned to the right controller, initiating interaction by capturing the robot's attention. If the robot is within an appropriate distance [13], it responds with an audio prompt saying "Is there anything I can help?" and acknowledges the human's request for attention by approaching. Subsequently, the human can pose the desired question by pressing the respective buttons on the controller, as illustrated in Figure 4.4.

4.3.2 Processing the Human's Response to Robot's Questions

When the robot receives a human response to a question, the most suitable result of the estimation among the estimation and prediction candidates is decided based on the human subject's response. The result depends on the combination of responses for the generated questions. In the case of the question, "Did you search here?", the human can respond in two ways, each of which is processed as follows;

- "Yes": the candidate on which the question was generated is used as the result of the estimation.
- "No": the candidate on which the question was generated is excluded.

For the inquiry "Where did you search?" the estimation outcome is determined based on the direction indicated by the human subject. The estimation result corresponds to the candidate whose direction aligns most closely with the indicated direction and the direction from the human position to the estimated candidate path's coordinates. Likewise, for the query "Where will you search next?" the prediction outcome is determined by selecting the option that closely aligns with both the direction indicated by the human and the direction from the human's position to the center the candidate path's coordinates. An example of this implementation from the human subject's perspective is shown in Figure 4.5.

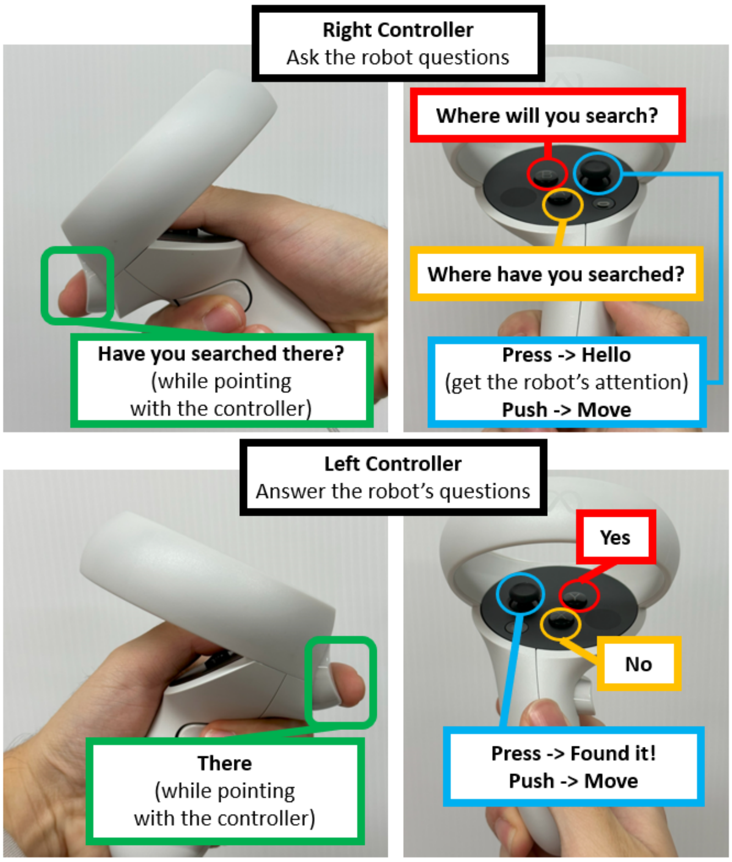

Figure 4.4: Controller mapping

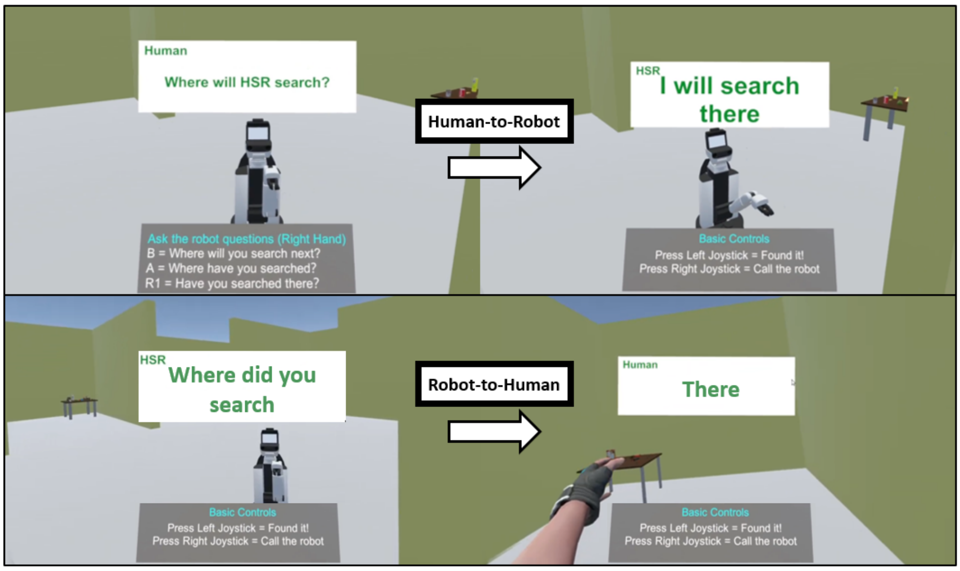

Figure 4.5: Interaction with the robot from the human subject's point of view

4.3.3 Processing the Robot's Response to Human's Questions

When the robot receives a call of attention from the human subject, the robot approaches to face the human and prepares to receive the question. When the question, "Where have you searched?" is asked by the human subject, the robot searches through its search history and responds to the question by pointing towards its most recent search destination. Conversely, when the question "Where will you search?" is presented, the robot refers to the LabelMap mentioned in Section X and based on its action planning, responds by pointing towards its next search location.

In the case when the question "Have you searched there?" while pointing is presented to the robot, the robot will match the human's pointing direction with locations that the robot has already searched. This is explained in detail in the next section.

An example of robot's response to the human's question is shown in Figure 4.5.

4.4 Handling Human Pointing Gestures

4.4.1 Pointing Gesture Matching

When the robot visits any desk or frontier, it will record and save the approximate coordinates of the target viewpoint and categorize them as a "desk viewpoint" or a "frontier viewpoint". In response to the "Have you searched there?" question presented by the human subject, we match the human's pointing gesture angle to the angle of the already traversed viewpoints and areas with respect to the human's current position.

In the case where the robot has one or more desk viewpoints saved, the robot will prioritize desk viewpoints and not consider frontier viewpoints, as they are less reliable in representing searched areas. If the human subject's pointing gesture matches the angle of the searched desk viewpoint, then the robot will respond positively to the question with "Yes, I have searched there". Else, if the human subject's pointing gesture does not match any known desk viewpoint, the robot responds negatively with "No, I have not searched there". A margin of error in the human's pointing gesture is also considered, and is defined as 20 degrees to the left and right of the desk viewpoint. An example of this implementation is shown in Figure 4.6.

If there are no desk viewpoints, the robot will instead match its previous frontier viewpoints. Similar to the previous situation, if the human subject's pointing gesture matches the angle of the traversed frontier viewpoint, the robot will respond with "Yes, I have searched there". Else, if the human subject's pointing gesture does not match any known frontier viewpoint, the robot responds with "No, I have not searched there".

4.4.2 Desk Clustering

Human's pointing gesture can be ambiguous. In this paper, we consider the possibility that the human subject may point to refer to a specific, individual desk, or point towards an area to ask whether multiple desks in an area has been searched. To enable the robot to respond to ambiguous cases, we cluster multiple desks together and declare the area between the desks as searched. The maximum size of the desk cluster is 3, and we define the searched area as the area that is within the outer vertex of each desk. An illustration of our implementation of the desk cluster is shown in Figure 4.7.

When the human subject points towards a desk cluster, as long as the angle of the pointing gesture is within the angles from the edges of the cluster to the current position of the human subject, the robot will respond positively with "Yes, I have searched there". With this, the robot will respond correctly to searched areas even if the human subject doesn't point directly at an individual desk.

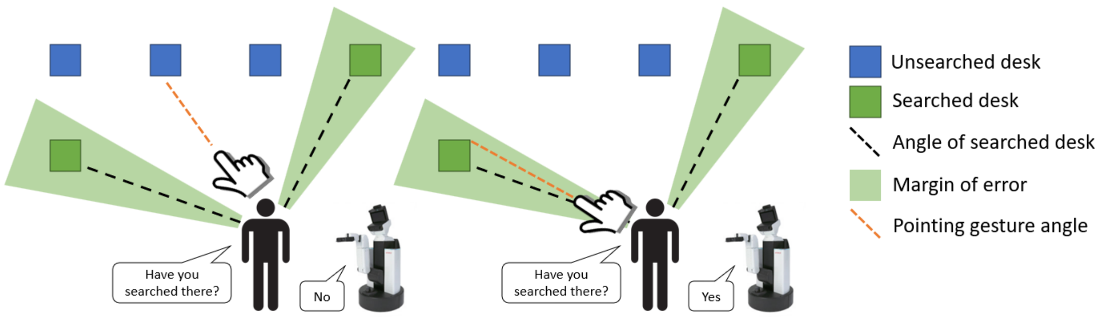

Figure 4.6: Example of point matching with searched desks

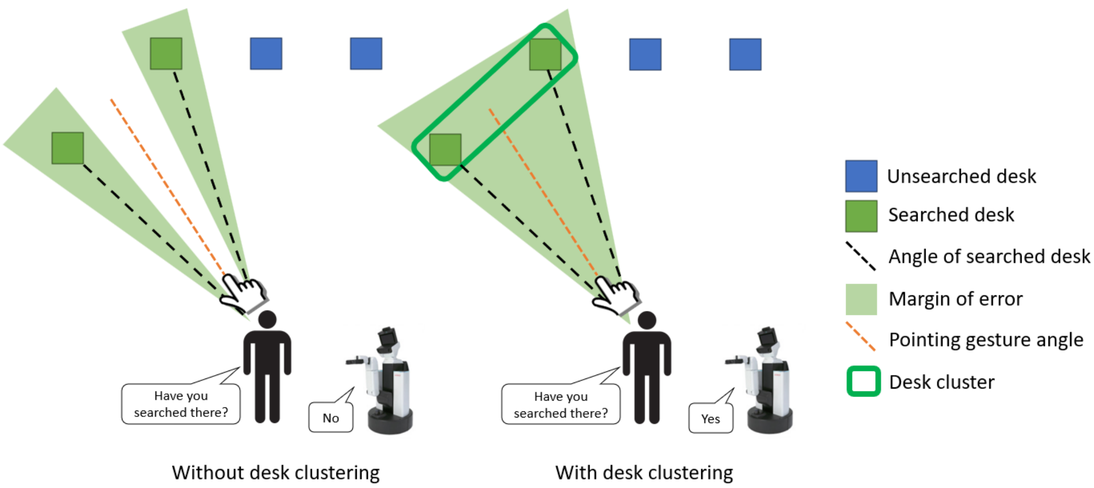

Figure 4.7: Example of the desk cluster implementation

5 Experiment

5.1 Simulator

In this study, we utilized SIGVerse [16] as the simulation environment, as illustrated in Figure 5.1. SIGVerse integrates ROS and Unity, providing a platform to simulate ROS topics and nodes on Unity, mirroring their implementation on an actual robot. Additionally, the simulation environment incorporates a head-mounted display, enabling the human subject to enter the simulated world as an avatar and interact with the robot through virtual reality (VR). The experimental robot employed is HSR [14].

To signal the system that the target object has been located, we instruct the human subject to press a button on the controller when they are within range and can visually confirm the search target through the head-mounted display. Conversely, the robot's recognition of both the search target and the human subject relies on YOLO [15]. For target object detection and retrieval, we consider the detection as erroneous if the distance between the human subject and the target object exceeds 3 meters, and the human subject reports the discovery of the target object, indicating the possibility of a false positive.

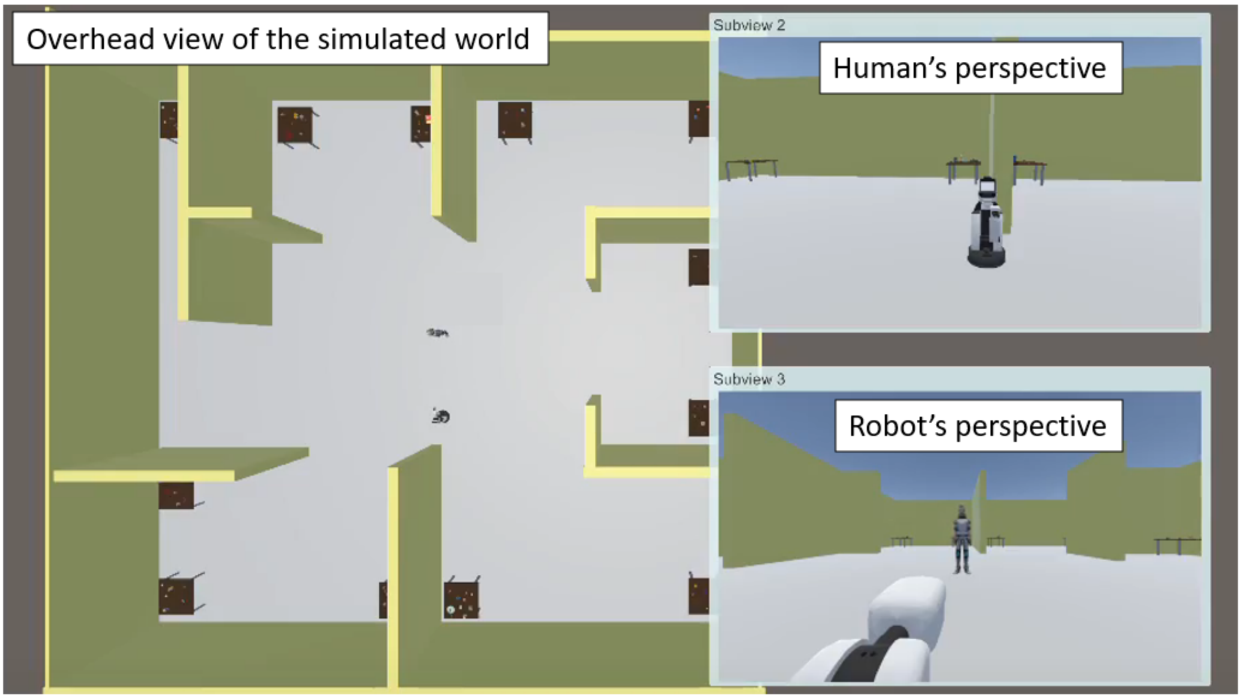

Figure 5.1: A snapshot of the simulated environment

5.2 Experiment setup

In the conducted experiments, three search objects were strategically placed within the search environment, and the task's completion required both the robot and the human to locate all of them. These objects were randomly distributed throughout the room. Participants were briefed that they would engage in a simultaneous search with the robot, and the robot would pose questions to them during the search, while also allowing them the freedom to inquire. Participants are instructed to search for three apples in the simulated environment. They are encouraged to respond to the robot's queries and, at their discretion, may pose questions to the robot when the experimental conditions permit. Proper operation of the controller for responding to questions is detailed in Section 4.3.

The study employed four comparison methods, each built upon the human movement estimation and prediction method as a foundation. Each method underwent testing with every participant, with the following descriptions:

- No Communication:
  No direct communication occurred between the robot and the human subject.

- Robot-Only Questioning:
  Only the robot had the authority to pose questions. In scenarios with multiple candidates for estimation and prediction, a decision was made by querying the human subject.

- Human-Only Questioning:
  Sole permission for asking questions was granted to the human. The robot refrained from posing questions, even when multiple candidates for estimation and prediction were generated.

- Bidirectional Communication:
  Both the human subject and the robot were allowed to ask questions.

5.3 Evaluation metrics

We used the following three evaluation metrics:

- Total Time Taken per Search Task:
  This metric assesses the duration subjects required to locate all target objects within the search task.

- Number of Duplicate Searches:
  This metric quantifies the instances in which either the robot or the human subject conducted searches on a desk that had already been searched.

- Total Distance Traveled by the Human and Robot:
  This metric gauges the cumulative distance covered by both the human subject and the robot throughout the search task. It takes into account that communication incurs a time cost and views the distance traveled as a representation of the combined effort exerted by both the robot and human to accomplish the search task.

5.4 Experimental Results

21 undergraduate and graduate students participated in the experiment. Figure 5.2 shows the results of search time in each condition. Figure 5.3 shows the results of the amount of duplicate searches in each condition. Figure 5.4 shows the results of the total distance cost for both human and robot in each condition. Examples of real search paths and final search areas for both the robot and human under each condition are illustrated in Figures 5.5, 5.6, 5.7 and 5.8. Table 5.1 shows the average search time, the average amount of overlapped search and the average cumulative distance cost by the robot and the human subject. Tables 5.2, 5.3, 5.4 shows the results of the two-way analysis of variance between each condition.

Comparing the search methods employed in our experiment, we observed notable improvements in search efficiency when communication was introduced, both in robot-only and human-only scenarios. Specifically, these methods exhibited a reduction in total search time, a decrease in the number of duplicate searches, and a decline in overall distance cost for both the robot and human subject. These findings align with the expectation that communication aids in better coordination and understanding between the human and the robot. Interestingly, bidirectional communication, where both the robot and human could ask questions, demonstrated mixed results. While there were observable improvements in the average number of duplicate searches and distance cost for both the robot and the human, the total time taken per search task did not exhibit a significant improvement.

Firstly, we discuss the effectiveness of one-way communication, examining the impact of robot-only communication, human-only communication, and no communication methods. The robot's consideration of human behavior and its avoidance of human-searched locations in the robot-only communication experiment contributed to a notable reduction in duplicate searches. By interacting with the human through questions, the robot accurately predicted and adapted to the human's search behavior, actively steering clear of previously explored areas. Similarly, in the human-only communication experiment, participants, with the ability to question the robot, effectively confirmed searched areas and adeptly avoided them, especially when the robot was out of sight during the search. These strategies collectively led to a decrease in the number of duplicate searches, consequently reducing the total time per search task. An example of the paths taken by the human and robot during this one-way communication is shown in Figures 5.6 and 5.7. Furthermore, the diminished occurrence of duplicate searches resulted in significant improvements in distance costs for both robot-only and human-only communication methods compared to the no communication method.

It should be noted that while the average time improvement was 5.33% for robot-only communication and 6.09% for human-only communication, the distance improvement was more pronounced, reaching 9.65% for robot-only communication and 19.94% for human-only communication. The difference in distance improvement can be attributed to the frequency of questions; the robot asked more questions in robot-only communication, leading to additional travel to and from the human. Conversely, in human-only communication, the human tended to ask questions only when the robot was encountered en route to the next search target. If an approach to the robot is necessary, the human is able to readjust and select another search target that is closer to the participant's current position after the questions were asked. These minor acts account for the significant difference in distance improvement between robot-only and human-only communication.

However, it's crucial to note that in the human-only communication method, some participants refrained from asking questions, either due to the robot's distance or a perceived lack of necessity. Despite this, participants actively avoided areas already searched by the robot more than in the no communication method. One possible reason is that by allowing the option open for humans to ask questions, participants became more proactive of the robot's whereabouts because of the need to locate and approach the robot for interaction, and avoided duplicate searches more than usual.

In the assessment of communication methods, we also analyze the efficacy of bidirectional communication in comparison to a no-communication approach. While we anticipated bidirectional communication to reduce the average search time similarly to one-way communication methods, the results showed a slight underperformance in terms of time taken. The bidirectional method takes, on average, 1.80% more time per search task than the no-communication method. However, the bidirectional method exhibited notable enhancements in diminishing the number of duplicate searches by 50%, and reducing the total distance covered by both human and robot by 15.33%. While the bidirectional communication method successfully prevented duplicate searches and lowered the combined effort of both the robot and human, the rise in average time taken implies that the predominant factor contributing to the reduced search efficiency was the time cost incurred during communication.

Our observations revealed two primary reasons for the prolonged communication time. Firstly, during the bidirectional communication, when the robot approached the human subject for a question, the human subject often reciprocated with a question, even when it might not have been necessary. Figure 5.8 illustrates an instance of the heightened number of approaches, where the robot paths exhibited increased erratic behavior triggered by question requests from the human subject and the robot's independent decisions to ask questions. This led to extended travel to and from the human, resulting in increased time costs and decreased distance cost efficiency. The average interaction time for bidirectional communication was 17.8 seconds, compared to 13.3 seconds for human-to-robot questions and 9.21 seconds for robot-to-human questions in one-way communication. In cases where both the human and robot were asking questions, the average interaction time for bidirectional communication increased to 23.7 seconds. This substantial difference significantly impacted time efficiency, outweighing the potential benefits of avoiding duplicate searches.

Secondly, the human subject tended to take longer to conclude dialogues due to possible control difficulty and confusion. The average time to conclude robot-to-human and human-to-robot dialogues in bidirectional communication was 15.9 seconds and 11.9 seconds, respectively. The need to respond to the robot's questions while concurrently presenting their own questions via the controller introduced a multitasking element, leading to participant confusion and extended interaction times. These factors collectively contributed to the reduced efficiency of the bidirectional communication method.

An unpaired t-test analysis was conducted in each experimental condition, comparing the no communication method against all other conditions, as presented in Tables 5.2, 5.3, 5.4. Our statistical analysis indicates that the presence of human communication exhibited the most significant differences, particularly in terms of duplicate searches and total distance cost. Conversely, for robot-only questions, the observed differences in total distance cost were statistically insignificant at p [illegible].05. Despite anticipating a notable improvement in total distance cost alongside the enhanced number of duplicate searches, the magnitude of the difference in total distance cost was insufficient to achieve statistical significance. One potential explanation for this phenomenon is the presence of inefficiencies in the action planning algorithm where the robot lacks a method to effectively weigh the benefits of seeking clarification from the human against the communication cost when deciding to pose questions, thus diminishing the potential advantages. We were also unable to establish a statistically significant difference in the time taken between all conditions. The lack of statistical significance in time taken is attributed to the exceptionally high variance in the results.

Table 5.1: Summary of experimental results

Communication	Average time taken [s]	Average duplicated searches	Average distance cost [m]
None	156.33	2.95	126.33
Robot-only	148.00	1.43	114.14
Human-only	**146.81**	**0.86**	**101.13**
Bidirectional	159.14	1.48	106.96

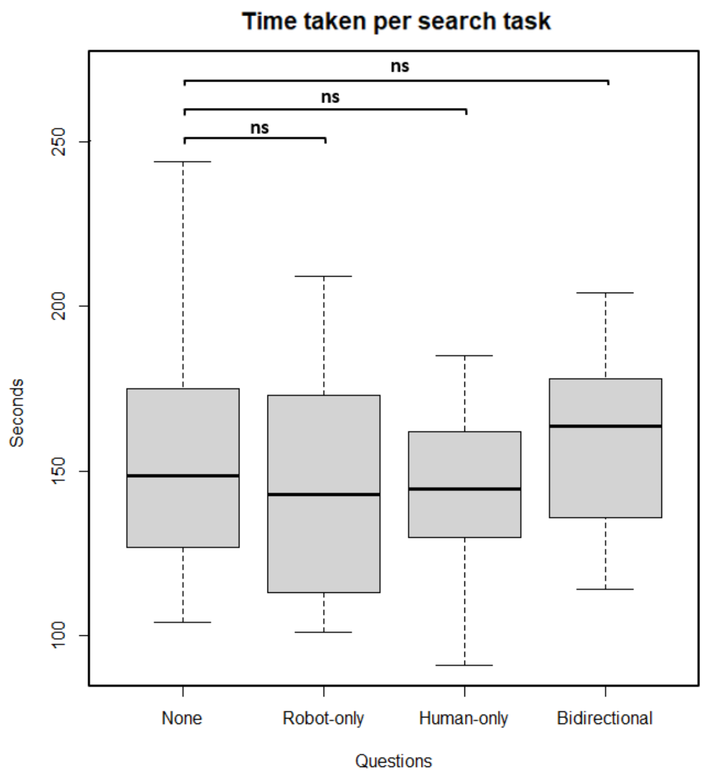

Figure 5.2: Total time taken per search task

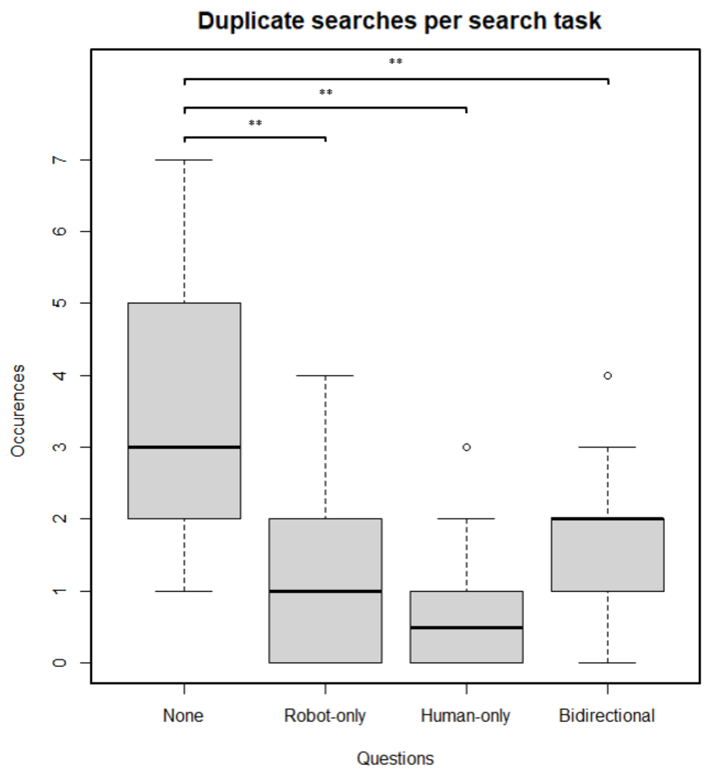

Figure 5.3: Total number of duplicate searches per search task

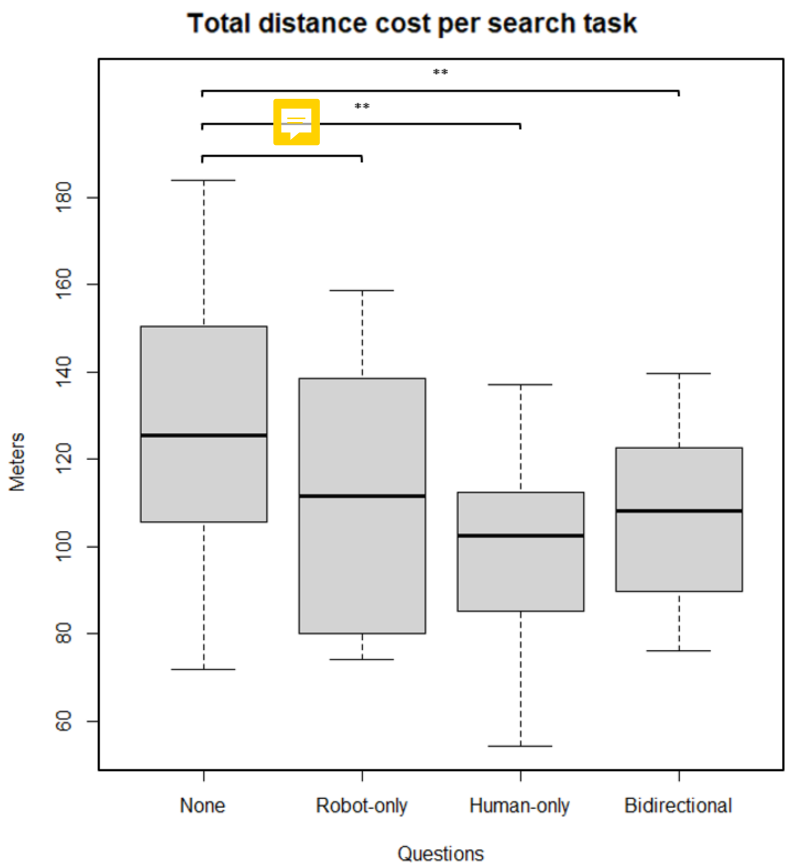

Figure 5.4: Total distance cost per search task

Table 5.2: Unpaired t-test result for total time taken per search task

Conditions	Degrees of freedom	t-value	p-value	
Robot-only	40	0.76303	0.224963	ns
Human-only	40	0.96416	0.170379	ns
Bidirectional	40	0.27752	0.391405	ns

Table 5.3: Unpaired t-test result for duplicate searches

Conditions	Degrees of freedom	t-value	p-value	
Robot-only	40	3.15305	**0.00153**	**
Human-only	40	4.69843	**0.000015**	**
Bidirectional	40	3.08462	**0.001844**	**

Table 5.4: Unpaired t-test result for total distance cost

Conditions	Degrees of freedom	t-value	p-value	
Robot-only	40	1.3801	0.087611	*
Human-only	40	3.10184	**0.00176**	**
Bidirectional	40	2.49159	**0.008482**	**

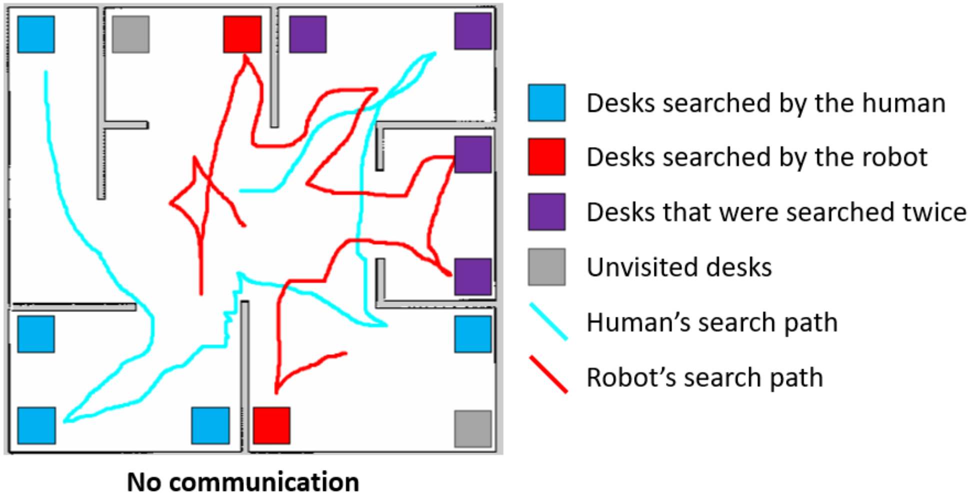

Figure 5.5: Sample results for the no communication method

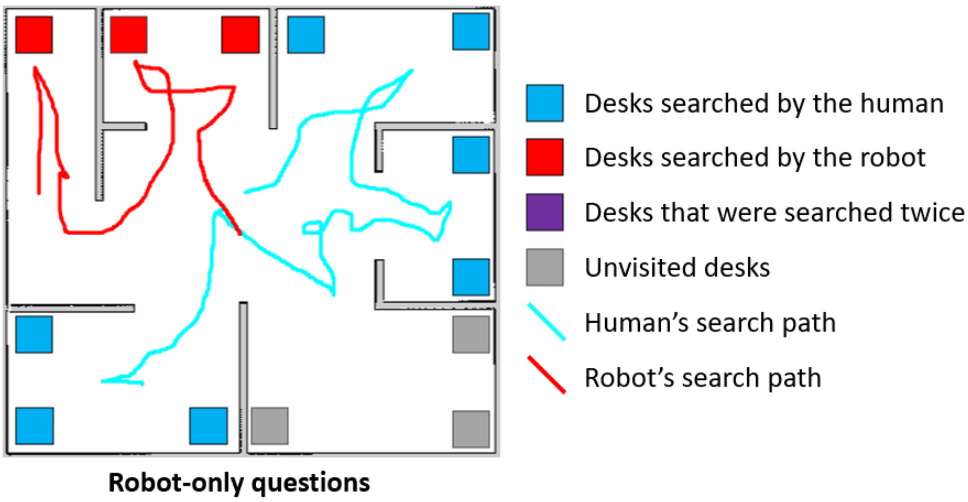

Figure 5.6: Sample results for the robot-only questions method

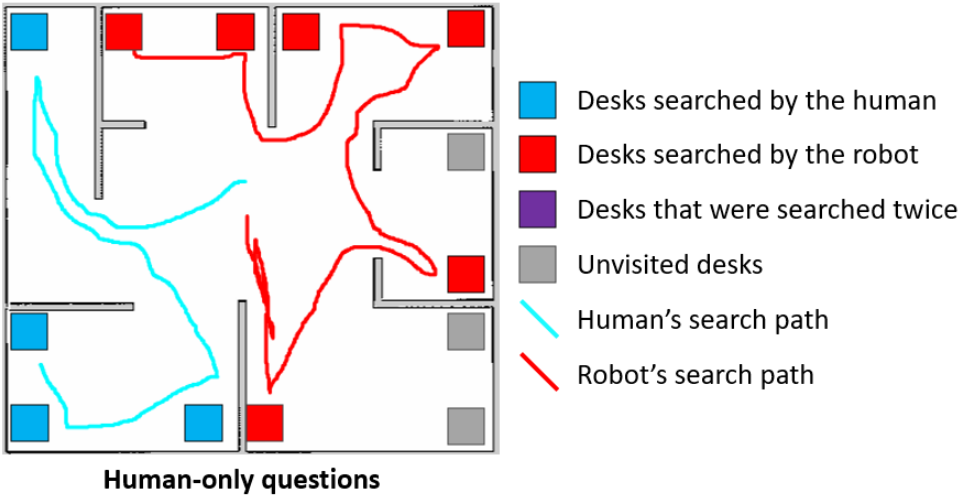

Figure 5.7: Sample results for the human-only questions method

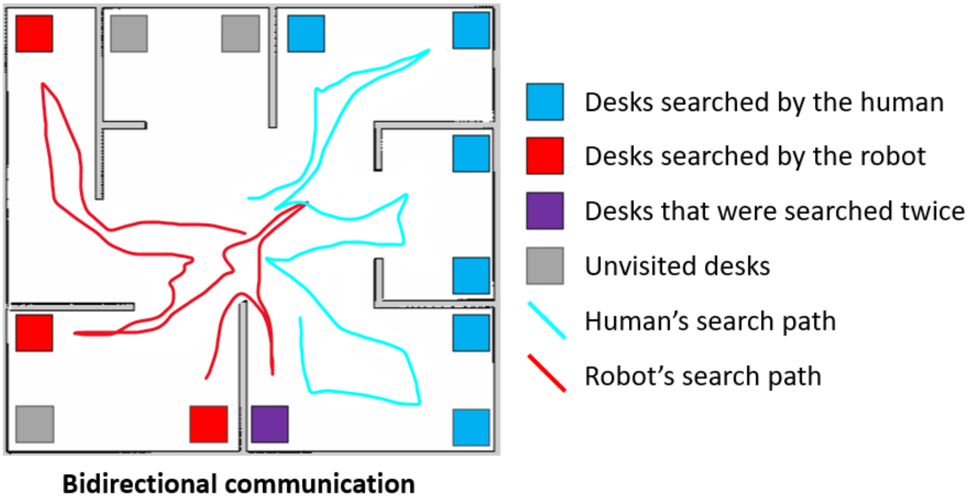

Figure 5.8: Sample results for the bidirectional communication method

6 Conclusion

6.1 Summary

In this study, we proposed a bidirectional communication method aiming to enhance human-robot interaction and improve joint object search efficiency. The method involves two-way dialogue to facilitate the human's anticipation of the robot's search behavior. We developed robot responses to human questions, incorporated searched desk angle matching, and implemented desk clustering to interpret human pointing gestures. Point matching determines if a desk pointed to by the human has been searched, while desk clustering designates an area between searched desks as explored. This approach minimizes human errors in revisiting already searched areas and promotes proactive engagement with the robot's search paths. The dialogue mechanism utilizes fixed messages and pointing directions. Simulation experiments demonstrated reduced duplicate searches, decreased total distance cost, and shorter search times, highlighting the effectiveness of allowing humans to query the robot about its search behavior. Simulation experiments demonstrated reduced duplicate searches and decreased total distance cost, highlighting the effectiveness of communication in seeking clarification of the counterpart's search behavior. However, it was observed that bidirectional communication is less effective than one-way communication in reducing search time, suggesting a complex interaction dynamic when both parties can pose questions.

6.2 Future Work

- Multiple responses for the robot's inquiry
  The existing pointing response is limited to indicating a single direction. However, in certain search environments and during extended periods when humans are not observable, providing only one direction may prove inadequate. Consequently, enabling the human response to sequentially specify multiple positions can enhance the accuracy of estimating/predicting candidates. This approach also offers the potential to reduce communication costs, as the robot doesn't need to pose questions as frequently when there are multiple answers to reference.

- Optimizing the robot's decision making
  Minimizing travel costs during dialogue is crucial for decreasing search time. To achieve efficient communication, the robot needs to determine the optimal timing for asking questions and strike a balance between communication costs and potential benefits. As questioning involves the robot approaching the human subject, it becomes imperative for the robot to choose the optimal time for approach, considering the surrounding situation and the positions of both the robot and the human subject.

- Improving simulation ease-of-use

  In our observations, we considered the impact of intricate controls on the average duration per interaction in the Bidirectional Communication method. Responding to the robot and posing their own questions can be challenging with the current controller setup. It is essential to either simplify the controls on the controllers or devise a more user-friendly communication interface for the simulation. Employing voice commands for asking and answering questions, instead of relying on button presses, might enhance communication with the robot, making it more intuitive and less complex.

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