The Amazing Race™: Robot Edition

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Abstract—State-of-the-art natural-language-driven autonomous-navigation systems generally lack the ability to operate in real unknown environments without crutches, such as having a map of the environment in advance or requiring a strict syntactic structure for natural-language commands. Practical artificial-intelligent systems should not have to depend on such prior knowledge. To encourage effort towards this goal, we propose The Amazing Race™: Robot Edition, a new task of finding a room in an unknown and unmodified office environment by following instructions obtained in spoken dialog from an untrained person. We present a solution that treats this challenge as a series of sub-tasks: natural-language interpretation, autonomous navigation, and semantic mapping. The solution consists of a finite-state-machine system design whose states solve these sub-tasks to complete The Amazing Race™. Our design is deployed on a real robot and its performance is demonstrated in 52 trials on 4 floors of each of 3 different previously unseen buildings with 13 untrained volunteers.

Index Terms—Behavior-Based Systems, Autonomous Agents, Cognitive Human-Robot Interaction, Autonomous Navigation

I. INTRODUCTION

THE Amazing Race™ is a popular reality television show in which two-person teams race to some designated location. They typically have to figure out where they are, navigate through foreign areas, and ask people for directions to their destination. State-of-the-art artificial-intelligence and human-robot-interaction research enables robots to solve such natural-language-driven navigation tasks [3, 5, 15, 16, 19, 21, 22, 22, 30]. However, these systems suffer from certain limitations such as requiring a specific syntactic structure for natural-language commands or requiring a map of the environment. A system design without these crutches is crucial for operating autonomously in new, unknown environments. Additionally, it is important for these systems to have productive interaction with humans for the purpose of receiving instructions to execute or to learn new information. However, it is impractical and inconvenient for every person to know the precise details of a robotic system in order to interact with it. Therefore, robotic system designs should be based on and thereby exhibit human-like behavior to enable natural and useful interaction with humans.

To drive research towards this outcome, we propose a novel challenge problem to the AI community: The Amazing Race™. The task is this: we place the robot in an unknown environment, without a map, and give it the name of a person, room, or building to find. For the purpose of constructing an initial solution to this task, we restrict the goal to finding a door with a specified number on a single floor of a building. Because the robot has no prior knowledge about the goal location nor the structure of the environment, it must seek a person for assistance. Once a person is found, the robot must engage them in a dialogue to obtain directions to the goal. It has to follow these directions to reach the hallway that the room is in, at which point it would have to systematically search for doors and read their door tags to locate the correct one. We present a novel finite-state-machine (FSM) system design that makes these logical steps to accomplish this task.

Our hypothesis is that this problem requires a specific set of abilities that are invoked in a particular order, equivalent to an FSM. We carefully chose a sequence of specific states for our FSM design that reflects the steps a typical person would take to efficiently find a room in an unknown office environment. Initially knowing nothing about the environment, many people would ask the first person they see for directions. After receiving these directions and potentially asking for clarification, they would follow them to the approximate location of the room and begin looking for the specific number. Our FSM design mimics this human behavior, which can result in a shorter and more efficient path to the goal as opposed to a simple exhaustive search of the environment. Although an exhaustive search would eventually succeed, it would not necessarily take the most efficient path, would ignore people who may have a rich understanding of the environment and a willingness to help, and would not push the envelope on robot cognition. Additionally, an exhaustive search becomes unsuitable as the size of the environment increases.

In order to enable such human-like reasoning, we abstract low-level sensor data such as audio, video, and LiDAR into information that a human would have readily available such as navigation directions and potential goal locations. The states in our FSM design, as shown in Figure 1, also referred to as behaviors, make use of this information to handle new and/or complex situations. They also incorporate methods to handle complete, partial, or erroneous information similar to how a human would when encountering such in conversation or navigation. We believe this design mimics high-level aspects of human behavior on the same task. Additionally, to the best of our knowledge, this paper makes the following novel contributions:

- It is the first to propose a method for constructing a navigation plan by extracting directions and intersections

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from spoken natural-language dialogue with a person. This navigation plan is executed by the robot using novel autonomous methods that ground directions and intersections in the map constructed by a SLAM algorithm.

- It is the first to propose a method for detecting, localizing, and inspecting doors to find the desired goal. It employs novel common-sense reasoning to efficiently search the environment for the correct door.

In order to evaluate the performance of our system, we conducted 52 trials across 4 floors of each of 3 buildings previously unseen by the robot. We recruited 13 untrained volunteers to provide the robot with directions to the specified goal room number in each trial. Due to our system’s ability to recover from individual behavior failures, we demonstrate a high success rate of 76.9%. Additionally, we document observations made during the trials as opportunities for further research into this task.

II. SYSTEM OVERVIEW

In this section, we provide a high-level overview of our system’s hardware, software, and architecture as well as the method used to construct a qualitative map from the quantitative map produced by SLAM. We provide detailed descriptions of our system’s components in the next section.

A. Hardware and Software

Our robotic platform consists of a Clearpath Husky A200™ UGV equipped with an Open IMU UM7, Velodyne VLP-16 3D LiDAR, Axis M5525-E PTZ Camera, Blue Yeti microphone, and a System76 Laptop with two Nvidia GeFor GTX 1080 GPUs. Each of these is a commercial, off-the-shelf product. Clearpath integrated the IMU, LiDAR, PTZ Camera, and laptop onto the Husky A200™ UGV.

Our software\textsuperscript{1} is implemented in a combination of C++ and Python, using ROS Kinetic as the communication framework between different components of the system. We use Google Cartographer\textsuperscript{17} to perform simultaneous localization and mapping (SLAM) from data from the IMU and 3D LiDAR. We record speech with the Blue Yeti microphone and convert it into text using the Google Speech-to-Text\textsuperscript{12} API. We use the Stanford Parser\textsuperscript{9} to parse the text. We use Python’s pyttsx3\textsuperscript{7} library to synthesize speech through the laptop speaker. We use YOLOv3\textsuperscript{25} to detect people in images taken from the Axis camera. We use LSD (Line Segment Detector)\textsuperscript{14} on images from the Axis camera as part of our method for detecting doors. We extract text from images of door tags taken with the Axis camera with Google’s Optical Character Recognition\textsuperscript{13} API. We use a LiDAR-camera calibration software package\textsuperscript{1} to compute a calibration matrix between the 3D LiDAR and the Axis camera. This matrix lets the system compute 3D locations for detected people and doors in the environment.

B. Architecture

Our architecture is a finite-state machine illustrated in Figure 1. This design makes logical steps towards reaching the goal and recovers from failure at any of those steps. Each state has a success condition that leads to the next state in the pipeline as well as failure conditions which result in a transition to the initial state of the system. Given a goal description, the initial state is WANDER, as the robot needs to find a person to get directions to the goal. This state allows the robot to explore the environment while simultaneously attempting to detect and track people. Once a person is found, the robot enters the APPROACH_PERSON state, in which it drives towards the person and synthesizes speech to grab their attention. If the robot successfully reaches the person, it initiates a conversation with them in the HOLD_CONVERSATION state. The robot uses speech synthesis and speech recognition to request directions to the desired goal and interpret the person’s response, respectively. It can ask an appropriate clarification question if the interpreted directions are incomplete. Once a complete set of directions are determined through dialogue with the person, a transition to the FOLLOW DIRECTIONS state is made. FOLLOW DIRECTIONS executes each direction in order by continuously mapping the environment to determine when to continue to the next instruction, such as turning left when a left turn becomes available. Successful completion of the directions implies that the robot is in the hallway that contains the goal. The robot then enters the NAVIGATE_Door state which involves detecting doors and driving up to them to inspect their door tags. This will let the robot ultimately confirm arrival at the desired goal.

C. Navigation Process

The physical environment has intersections connected by hallways. Humans give navigation instructions by describing paths through hallways between intersections. They use informal terms to classify intersections into various types (e.g., elbow, three-way, and four-way) and to distinguish between different hallways emanating from intersections by their heading (e.g., forward, left, and right). To facilitate the interpretation of these informal navigation instructions, our robot constructs and maintains two maps of the environment,
One quantitative and one qualitative. The *quantitative map* is an occupancy grid constructed by SLAM. It is a 2D matrix of cells, where each cell corresponds to a 5 cm square of the ground that takes one of three possible classifications: *free*, *obstacle*, or *unknown*. Generally, in an indoor office environment, free cells would be rooms or hallways, obstacle cells would be walls or objects, and unknown cells would be unexplored areas of the building or anything outside of the walls. The *qualitative map* is a graph whose vertices represent detected intersections labeled with intersection type and whose edges denote detected hallway paths. We refer to these as *registered* intersections and hallway paths since the process of constructing and maintaining the qualitative map can add, remove, merge, and update registered intersections and hallway paths when detecting new ones. The qualitative map, along with the robot’s current pose (position and orientation) in that map, is continually maintained and updated by a background process running SLAM. The qualitative map is constructed and updated from the quantitative map and robot pose by a background process continually running at 1 Hz. We refer to the latter background process as the *navigation process*. The qualitative map produced by the navigation process is used by several of our robot behaviors.

1) Trajectory Generation: The first step of the navigation process is to construct various sets of trajectories, short paths that the robot can drive from its current pose. A trajectory is a target point in world coordinates at a specified distance and heading from the current pose. Low-level robot navigation uses trajectory target points as driving instructions. We nominally consider all distances that are integral multiples of 1.2 m from 1.2 m to 7.2 m, combined with all headings that are integral multiples of $\frac{360}{64}$°, as *potential trajectories*. These are filtered as follows. We first remove all trajectories which require traversing a point that is within 0.6 m of an obstacle or unknown space to reach the target point. This yields a set of *drivable trajectories*. The 0.6 m threshold was chosen as it is our robot’s circumscribed radius; it would not fit through passageways smaller than this. Since we need to search each trajectory for obstacles, the 1.2 m quantization was chosen to reduce the number of potential trajectories considered while still considering sufficiently many to successfully interpret and execute human navigation instructions. We then filter the set of drivable trajectories, keeping only the ones with the largest distance for each heading. This yields a set of *maximal drivable trajectories*. Finally, we label each maximal drivable trajectory with one of eight *qualitative directions* based on its heading (Figure 2a). We then filter the set of maximal drivable trajectories, keeping at most a single trajectory for each qualitative direction, the one with the median heading. This yields a set of *qualitative drivable trajectories*, there being at most eight of these, each labeled with a distinct qualitative direction. Figure 2(b) illustrates the process of trajectory generation.

2) Intersection Detection and Classification: The next step in the navigation process is to determine whether the robot is in an intersection, and if so, to determine the type of that intersection (e.g., *elbow*, *three-way*, or *four-way*). It does this at multiple scales, with each distinct trajectory distance taken as a scale, to tolerate different building designs with different hallway lengths and widths (Figure 3).
Fig. 3: (a) These intersections, with very short hallways, can only be detected with a distance ≤2.4 m. (b) This corner, with a decorative front to a lab space, can only be detected with a distance ≥4.8 m. All intersections are correctly detected and classified by considering multiple distances.

At each scale, this process starts with all drivable trajectories at that scale. The first step is to eliminate drivable trajectories that would not be considered as driving through hallways. This is done by grouping all adjacent drivable trajectories (with headings differing by $\frac{360^\circ}{m}$) to represent a traversable area (Figure 2c). The width of a traversable area is determined as the maximal Euclidean distance between any two target points of drivable trajectories in the traversable area. If a traversable area is wider than the specified width of a hallway for that building, all trajectories associated with that traversable area are discarded. This allows the robot to ignore alcoves and similar open spaces, and yields a set of hallway trajectories.

The hallway trajectories are grouped into pairs, triples, and quadruples whose headings are $\approx 90^\circ$ apart. These constitute potential intersections of type elbow, three-way, and four-way, respectively. Each such tuple constitutes a potential intersection. Potential intersections whose elements are not separated by obstacles are discarded. This yields a set of intersection candidates, each of which has the robot’s position as its initial location. Intersection candidates are scored based on the sum of the distances of the location and each element’s target point from the nearest obstacle.

This process may produce multiple intersection candidates, e.g., an elbow will always be present when a three-way is also present and an intersection candidate produced at a larger scale may also be present at a smaller scale. The navigation process prioritizes intersection candidates as follows: a) quadruples over triples, b) triples over pairs, c) larger scales over smaller scales, and d) higher scores over lower scores. This yields at most a single detected and classified intersection at the current robot position. For reasons to be discussed later, each detected and classified intersection is given a unique identifier and each hallway trajectory in that intersection tuple is also given a unique identifier.

As an example, consider Figure 2(d), which illustrates intersection detection and classification at a single scale, namely 3.6 m. Three pairs of hallway trajectories (green, blue, and orange) are shown (out of a possible nine), each hallway trajectory associated with the highlighted (green, blue, and orange) target point. Each such pair constitutes an intersection candidate. Pair 2 (blue) will have the highest score (since its target points are furthest from obstacles) and will be kept as the single detected and classified intersection.

3) Intersection Refinement: Since the navigation process performs intersection detection and classification repeatedly at 1 Hz, it can detect the same intersection multiple times, particularly if the robot remains in an intersection for more than 1 s. This is akin to how object detectors can place multiple but different boxes around an object. We address this by performing a kind of nonmaximal suppression (NMS) in a fashion analogous to how object detectors deal with this problem. Moreover, intersection detection and classification is performed relative to the robot pose. As this changes, the classified intersection type might change due to noise (e.g., classifying an intersection as an elbow when it is a three-way). Further, through a process described below, detected and classified intersections are registered as vertices in the qualitative map. Registered intersections are labeled with their location, which we wish to be the center of the physical intersection. However, detected intersections are registered with their location being the robot position at the time of detection, which might not be the center of the physical intersection.

To address this, we perform intersection refinement. We suppress detection of new intersections when the robot is within 2 m of a registered intersection. Further, we continuously refine the locations and classification labels of registered intersections in a background process. This process recomputes the intersection candidates while imagining the robot to be at every point in a $3 \times 3$ grid, with 0.4 m spacing, centered on the current location of each registered intersection, using the current SLAM occupancy grid. The intersection candidates are pooled and prioritized as in initial intersection detection and classification to yield a single redetection and reclassification.

The registered intersection is updated to reflect the redetected and reclassified intersection, including its location. We enforce a constraint that intersections cannot shift more than 2.4 m from their original location. For efficiency, this refinement is only applied to a registered intersection when the robot is within 5 m of that intersection.

Each detected and registered intersection contains a) its location, b) its type, and c) a tuple of hallway trajectories. The hallway trajectories represent the hallway paths between intersections. During refinement, the redetected intersection might contain different hallway trajectories than the current registered intersection. This can happen when, for example, a group of people stop to talk and block a hallway trajectory in the intersection. During intersection refinement, we wish to maintain the same unique identifiers associated with each intersection and hallway trajectory in that intersection. This requires constructing a correspondence between the hallway trajectories in the registered intersection and those in the redetected intersection. The optimal correspondence is found with the Hungarian algorithm [20] applied to a bipartite graph whose left vertices are the hallway trajectories in the registered intersection, whose right vertices are the hallway trajectories in the redetected intersection, and whose edges are given a cost which is the angular distance between the hallway trajectory headings. Edges in this bipartite graph...
A. Wander

Wander is the initial state of the system and lets the robot continuously navigate through the environment, trying to detect and track people until it finds an approachable person. The general strategy is to explore the environment in a human-like manner, usually moving forward, choosing a direction to go when at an intersection, and only turning around when reaching a dead end.

1) Wander Substates: The Wander state has five substates: a) Make_Decision, b) Rotate_Recovery, c) Rotate, d) Drive_Forward, and e) Drive_Through_Intersection. Wander enters the Make_Decision substate first, where it analyzes whether it is in a registered intersection and which qualitative directions are available. If no qualitative directions are available (e.g., when it is first initialized), it enters the Rotate_Recovery substate, which causes it to spin in place 360°. This substate helps to update the quantitative and qualitative maps in the immediate vicinity, which determine whether any qualitative drivable trajectories are available. If none are available, it stays in this substate. If qualitative drivable trajectories are available, the robot selects the one whose heading is closest to its current orientation as the recovery angle. The robot enters the Rotate substate to match its orientation with that of the recovery angle and will then enter the Drive_Foward state. This series of substates helps it find its way out of alcoves, entrances, or elevator landings and into hallways.

When in the Drive_Forward state, the robot continuously drives forward while monitoring for registered intersections. This forward, which we use to indicate when and how a robot drives down a hallway, is distinct from the qualitative drivable trajectory forward and will be explained in Section III-A2. When it enters a registered intersection, the robot enters the Make_Decision substate to determine what to do. First, it determines which hallway trajectory it entered the registered intersection from. Hallway trajectories included in registered intersections maintain a visitation time as an indication of when they were last visited. The visitation time for the hallway trajectory used to enter the registered intersection is updated to the current time. Then, it temporally orders all active hallway trajectories of that registered intersection. If it has visited each hallway trajectory, it selects the oldest one and takes it. If there are one or more hallway trajectories that it has not taken, it randomly selects one and takes it. It then updates the visitation time of the selected hallway trajectory with the current time. Maintaining visitation times allows the robot to explore the environment in a thorough manner, preferring to visit areas in the map that it has not seen or that it has seen least recently.

After selecting the hallway trajectory to take, if the hallway trajectory is to the left or right of the robot’s pose, the robot will enter the Rotate substate to rotate 90° to the left or right, respectively. Thereafter, or in the case that the robot chose to drive straight through the intersection, it enters the Drive_Through_Intersection substate to move out of the intersection and into the hallway. This substate prevents the robot both from immediately recognizing it is in a registered intersection and causing it to re-evaluate what to do.

III. States of the System Architecture

In this section, we describe the the implementation of each state in our system.

are only created when the angular distance is <30°. This correspondence is used to reassign the unique identifiers from the hallway trajectories in the registered intersection to those in the redetected intersection.

As described previously, a redetected intersection may have different type than a registered intersection, and thus may have a different number of hallway trajectories. Thus, the correspondence as produced above may fail to assign a hallway trajectory from the registered intersection to one in the redetected intersection either because the redetected intersection is of a different type with fewer hallway trajectories or because of eliminated edges. A hallway trajectory in the registered intersection that does not have a corresponding hallway trajectory in the redetected intersection is maintained, with its unique identifier, in the registered intersection in a deactivated state, so that it can be reactivated later with the same unique identifier.

4) Intersection Graph: The unique identifiers associated with registered intersections and their hallway trajectories, whose consistency is maintained over time by intersection refinement, allow us to construct a graph to represent the qualitative map. When the robot comes within 0.5 m of a registered intersection, it selects the hallway trajectory whose target point is closest to the robot position as the one used to enter the intersection. The robot’s path is searched backward until it comes within 3 m of a hallway trajectory from the last registered intersection it visited. An edge in the qualitative map is registered between these two registered intersections and represents a hallway path. The weight of this edge is taken as the Euclidean distance between the locations of the two registered intersections. If the backward search process does not produce a hallway trajectory, that hallway trajectory is left unconnected, to represent hallways that have not been completely explored yet. This graph is continually constructed and updated by the navigation process. See Figure 4 for an example of the qualitative map produced for a single floor of a building.

Fig. 4: Qualitative map produced for a single floor of a building. The red line indicates the path that the robot traveled. Blue spheres are registered intersections. Yellow arrows are hallway trajectories associated with each registered intersection.
The `DRIVE_THROUGH_INTERSECTION` substate has the robot drive `forward` continuously. Once it has traveled more than 2 m and the intersection type has changed, the robot returns to the `DRIVE_FORWARD` substate.

If, while driving `forward`, the robot reaches a dead-end (which is determined by there being a back qualitative drivable trajectory but no forward, left, or right qualitative drivable trajectories), the robot performs a single 360° spin to ensure that it truly is at a dead-end (instead of simply having failed to detect an adjoining hallway). After performing this spin, it will enter the `MAKE_DECISION` substate, which, if it is still at a dead-end, will enter the `ROTATE_RECOVERY` substate. This substate will see that there is a single qualitative drivable trajectory available (back), which it uses as its recovery angle. The robot would enter the `ROTATE` substate, rotate 180°, and then return to the `DRIVE_FORWARD` substate. These substates can be modeled as a FSM as shown in Figure 5a.

2) `Forward Driving Goals`: When the robot starts driving down a hallway, it might not be in the middle of the hallway, and its orientation might not match that of the hallway. Despite starting in a suboptimal pose, we want the robot to move towards and drive down the middle of the hallway. To do so, when the robot enters the `DRIVE_FORWARD` substate, we take its current orientation as the `forward orientation`. This `forward` orientation will get refined over time as the robot drives down the hallway to more accurately reflect the same orientation as the hallway.

While the navigation process provides a set of qualitative drivable trajectories, due to the suboptimal starting pose of the robot, there may not be a qualitative drivable trajectory associated with the `forward orientation`. Therefore, we pass the `forward` orientation and a `cone angle` to the navigation process, ask it to find all maximal drivable trajectories within that cone and return the median one as the `median drivable trajectory`. Initially, the cone angle is ±15° from the `forward orientation`. If no drivable trajectories are found within the cone, this process is repeated with a cone angle of ±30° and then ±45°. When drivable trajectories are found within the cone, the median drivable trajectory is used as the `forward driving goal`.

This gets the robot moving towards the middle of the hallway and having its orientation more closely reflect that of the hallway. As it nears this first driving goal, these steps are repeated, but only up to a window of ±30°. After nearing its second driving goal, the robot is typically in the middle of the hallway and has the same approximate orientation as the hallway. For all remaining `forward` driving goals after this point, only a window of ±15° is used. Decreasing the maximum possible window after navigation to the first and second driving goals is done to avoid `forward` driving goals that lead to undesirable behavior. As the robot drives down a hallway, there may be alcoves on the left or right. If a wide cone angle is used, drivable trajectories can be within the alcove and the median drivable trajectory that is returned from the navigation process can cause the robot to veer off from the center of the hallway. In the worst case, it can drive into the alcove, have no qualitative direction `forward`, and think it has arrived at a dead-end. Alternatively, if instead of there being an alcove, there is a hallway, the robot can inadvertently drive around a corner (without realizing it) and still think it is driving `forward`. See Figure 6 for an illustration of this entire process.

Earlier, we stated that the `forward` orientation is updated over time to more accurately reflect the same orientation as the hallway. At first blush, it may seem logical to always use the robot’s current orientation as the `forward` orientation. However, this fails under the following scenario. As the robot drives down a hallway, obstacles may appear in front of it (e.g., people walking and/or sometimes stopping in front of it)—whether unintentionally or intentionally—to see how the robot will react). Standard local path planners handle these types of unexpected obstacles by navigating around them. As the robot is driving around such an obstacle, its orientation may change significantly such that it no longer matches that of the hallway and in some cases can be nearly perpendicular to the hallway. If, at this moment, the robot needed to update its driving goal, and used its current orientation as the `forward` orientation, the navigation process could either determine that there were no drivable trajectories or return a drivable trajectory that would move the robot in a direction it should not go. Either could derail the robot from properly driving down the hallway.

(a) The `WANDER` finite-state machine.

(b) The `FOLLOW_DIRECTIONS` finite-state machine. Transition conditions in Courier represent the next step in the plan. All others represent transition conditions derived from sensor data.

Fig. 5: Finite-state machines internal to the `WANDER` and `FOLLOW_DIRECTIONS` states.
To handle this case, once the robot has moved 2 m from its starting point, we compute the angle from its starting point when it began driving down to the hallway to its current position and use this as the forward orientation. This gives a much more accurate approximation of the orientation of the hallway and makes the forward orientation robust to the situation described above.

There is one additional mechanism we employ to help the robot drive forward around obstacles but we will postpone that discussion until Section III-D3 as it makes more sense in that context.

3) Person Detection and Tracking: The ultimate goal of the WANDER state is to locate a person to approach. Therefore, while the robot is navigating through the environment, it uses the Axis camera and 3D LiDAR to continuously detect and track people in that environment.

YOLOv3, a real time object-detection system, is used to detect people. It can detect multiple objects of different classes and provide their spatial location via bounding boxes. These boxes are used to determine the location of people in the quantitative map.

The camera’s horizontal field of view angle and resolution are known. Each pixel in the camera can be mapped to a particular angle relative to the position of the camera. These angles can be used to extract the distance of the detected object from the LiDAR data. Because bounding boxes from object detectors are imperfect, and because standard object detectors localize detections with boxes even though the shape of most natural objects (e.g., humans) is not rectangular, some of the LiDAR points will shoot beyond the object and hit a more distant object or wall. Instead of taking the average of these points, we keep the closest one, which represents the nearest part of the detected person. By knowing the pose of the robot, camera, and LiDAR, we can determine the precise position of that object in the quantitative map.

These person detections, along with their quantitative map coordinates, are fed into a detection-based tracker. Typically, a detection-based tracker combines bounding boxes from adjacent image frames into tracks if their pixel coordinates sufficiently overlap. However, in our case, this method is unsuitable because the robot is constantly moving. Therefore, instead of combining detections that occupy the same spatial region in the camera’s field of view, we combine detections that occupy/overlap the same location in the quantitative map. In this way, if the robot moves or rotates, the moving field of view does not affect the ability of the tracker to accurately piece together detections into tracks.

For all existing tracks, we compute the Euclidean distance from the last known location to each new detection. These distances constitute the cost to pair the track with the detection. We use the Hungarian algorithm to minimize the cost across all pairings of tracks with new detections and find the optimal pairing. We perform a sanity check to make sure that no pairings are unreasonable. We first determine the walking speed of the person, by computing how far they have traveled since the last detection and dividing that by the amount of time that has elapsed since then. If the walking speed is >2.5 m/s, we break the track-detection pairing and the detection becomes a new track. All pairings that meet this threshold are combined into a single track. Because detectors can be noisy and imperfect, the tracker employs forward projection on all tracks for up to 0.5 s to compensate for missed detections. Any tracks that go 0.5 s without an additional detection are pruned.

Tracks are classified based on the length of time they have been active and the average walking speed of the person. Once a track is ≥1.5 s long, the average walking speed is computed over the previous 1.5 s. The person’s walking direction is determined by whether the most recent location is closer to the robot than the location ≈1.5 s ago. If the most recent location is closer by more than 0.3 m/s, the person is considered approaching the robot. If the most recent location is further by more than 0.3 m/s, the person is considered walking away. Otherwise, the person is considered stationary. Tracks that are <1.5 s long are considered as having just begun and are thus ignored as part of any decision making on the part of the robot. Sample outputs of each of these four situations are shown in Figure 7.

Tracks that are classified as stationary or approaching the robot are considered “approachable.” When such occurs, the robot transitions to the APPROACH_PERSON state.

Fig. 6: Example of how the robot determines a forward driving goal despite starting with a suboptimal pose. The robot is 1 m from the wall and its orientation is ≈45° off from that of the hallway. The transparent red cone indicates that the navigation process was unable to find any drivable trajectories using a cone angle of ±15° from the forward orientation. The transparent blue cone indicates that the navigation process was able to find a drivable trajectory using a cone angle of ±30° and thus a cone angle of ±45° is not required. The median drivable trajectory that the navigation process returned is used as a forward driving goal (labeled “Driving Goal 1”). Upon approaching that driving goal, the robot repeats this process, but only up to a cone angle of ±30° if necessary, and the yellow arrow labeled “Driving Goal 2” will be its second forward driving goal. This process incrementally moves the robot to the center of the hallway and changes its orientation to more closely match that of the hallway.
Once an approachable person is successfully located, the system enters the APPROACH_PERSON state to introduce itself to the person, drive up to them, and face them just as a human would. Using the person’s location in the quantitative map, the robot computes a driving goal that is 0.8 m from the person (in a direct path from the robot to the person) with a pose that is facing the person, and begins driving there. If the person is approaching the robot, once they are within 7 m, the robot will hail them and ask them for help. When the robot is \( \leq 2 \) m from the person, it will introduce itself to initiate the conversation.

Throughout this process, the person’s location in the quantitative map is being monitored and updated, and new potential driving-goal locations are being computed. If any of these are \( \geq 0.5 \) m from the previous driving goal, the robot updates its driving goal. This allows the robot to approach the person in a closed-loop fashion. If instead of stopping, the person chooses to walk up to the robot, once they are within 0.8 m of the robot, the robot will immediately stop and consider this as having successfully approached the person. It will continue the process of monitoring and updating the driving goal until it either reaches the person, they leave the field of view (e.g., enter a room), or begin to walk away. If either of the latter two scenarios occur, the robot will begin this entire process over with the next-closest approachable person. If there are none present, it returns to the WANDER state.

C. HOLD_CONVERSATION

Once the robot approaches the person, it enters the HOLD_CONVERSATION state whose objective is to construct a plan of how to navigate to a specific destination by engaging in dialogue with the person. This plan is represented as a list of navigational actions that can be executed by the robot as commands. If the person were to formally communicate the plan to the robot, this task would be trivial. What makes this nontrivial is that the communication is done informally through spoken natural language.

Inferring a plan from spoken dialogue with a person presents several challenges. First, people often ramble and speak incoherently. Second, Google’s Speech-to-Text API is imperfect and sometimes returns incorrect and/or nonsensical results. Third, state-of-the-art parsers, trained on written text rather than spoken text, create abnormal parse trees that make extracting relevant and accurate information more difficult.

To overcome these obstacles, we employ the following general approach to plan inference, i.e., constructing a plan from natural-language dialogue. We maintain a plan that consists of a sequence of steps, that are filled with actions of various kinds, including directions, intersections, and goals. Steps in the plan may be unfilled, denoted by □. Initially, the plan consists of a single unfilled step. The current (partial) plan is used at every dialogue turn to generate a query to the person. The response is processed in the context of the current (partial) plan to fill in unfilled steps, potentially add new steps that are either filled or unfilled, and potentially change or delete steps. This processing takes two forms. One is a sequence of steps for filling in parts of the plan based on the person’s response. The other is a set of rewrite rules that update parts of the plan based on the local context in the plan. If, after processing, the plan contains one or more unfilled steps, a new query is generated for the person and processing continues. This process continues until the plan contains no unfilled steps. To prevent an indefinitely long conversation, the length of the plan is restricted to ten steps. If a plan gets to that length, the robot ends the conversation, executes those steps, then searches for another person to ask.

The sequence of plan actions must be coherent. The rewrite rules attempt to render plans coherent. For example, if the plan indicates that the robot eventually reaches an elbow in the hallway, it would be incoherent for it to drive straight at the elbow. The robot uses its current knowledge to formulate and pose a query about a missing piece of information. The person’s response might provide information about one or more steps, or change a step that was incorrect. Rewrite rules are applied to fill in or modify steps that may not have been explicitly given but were implied. This process is repeated until a complete plan is constructed.

1) Spoken Communication: Our robot converses in real time, adhering to the norm of taking turns while talking
and using common sense to factor in previous utterances into subsequent utterances. Speech recognition and speech synthesis are mutually exclusive operations so a person’s response is only processed when they finish speaking.

2) Information Extraction: In the HOLD_CONVERSATION state, the robot attempts to fill in the steps of a plan with actions from a natural-language utterance. Our plans are formulated with a certain plan structure that stipulates that adjacent steps form pairs that constitute commands to the robot. The first step in a pair must be a direction action. The second step in a pair will be a stop condition and take the form of either an intersection action or a goal action. Only the last step in the plan can be a goal action. All other stop conditions must be intersection actions. Thus a plan can be thought of as a sequence of commands, each command being a direction for the robot to drive in until the specified stop condition, with the robot ultimately checking that it has reached the goal. The various actions that can fill plan steps of various kinds are shown in Table I.

Prior to any dialogue, the plan is initialized with a single empty step: \(\square\). In order to populate the plan, the robot’s first question to the person is ‘Can you tell me how to navigate to (destination)?’ The steps used to parse the response and populate the plan with actions are illustrated in Figure 8. First, the utterance is chunked by splitting it at key elements such as ‘.’ or ‘then.’ Each chunk is fed into the Stanford Parser. This results in more accurate parse trees than feeding the whole utterance into the Stanford Parser. Then, the parse trees are searched for phrases that contain direction keywords (e.g., ‘turn around,’ ‘left,’ or ‘right’) to insert the corresponding actions into the plan. If no direction keywords are found, the utterance is searched for any intersection or goal keywords to insert the corresponding actions into the plan.

Each phrase that contains one of the direction keywords is concatenated with its preceding and succeeding phrase to provide context for information extraction. Starting with the leaf node in the parse tree that corresponds to the direction keyword, the tree is searched for the nearest parent with one of the following POS tags: ADJP, ADVP, CONJP, FRAG, INTJ, LST, NAC, NP, NX, PP, PRN, PRT, QP, RRC, UCP, VP, WHADJP, WHAVP, WHNP, or WHPP. The trees corresponding to the left and right siblings of this parent node are used as the preceding and succeeding phrases, respectively. The preceding phrase is further refined by searching for the first verb that precedes the direction keyword; if that does not exist, we search for the first preposition that precedes the direction keyword. All words preceding the verb or preposition are eliminated from the preceding phrase. If no verb or preposition is found, no preceding phrase is used. In the event that the direction keyword’s parent has no left or right siblings, we use the entire tree from the chunk as the concatenated phrase.

\begin{table}
\centering
\begin{tabular}{|c|c|}
\hline
Kind & Action & English description \\
\hline
\hline
\textit{dir} & forward & drive \textit{forward} until a stop condition is encountered \\
& left & rotate 90° left \textit{left} \\
& right & rotate 90° right \\
& turn-around & rotate 180° \\
& either & left or right depending on availability \\
\hline
\textit{int} & elbow & intersection of type \textit{elbow} \\
& three-way & intersection of type \textit{three-way} \\
& four-way & intersection of type \textit{four-way} \\
& int-L & intersection with a left hallway trajectory \\
& int-R & intersection with a right hallway trajectory \\
& int-F & intersection with a left and/or right hallway trajectory, as well as a \textit{forward} hallway trajectory \\
& end & intersection with a left and/or right hallway trajectory, but \textit{not} \textit{forward} hallway trajectory \\
\hline
\textit{goal} & goal-F & goal is somewhere up ahead \\
& goal-L & goal is somewhere up ahead on the left \\
& goal-R & goal is somewhere up ahead on the right \\
& person & our next task is to find a person for further directions \\
\hline
\end{tabular}
\caption{Various kinds of actions that can fill plan steps as produced by HOLD_CONVERSATION.}
\end{table}

Otherwise, the direction keyword, direction determiner, in-}

These properties of plan structure allow us to formulate patterns to describe all minimal invalid action sequences. Each such invalid action sequence can be rendered valid by appropriately adding, deleting, or modifying plan steps. Such plan modification is performed by rewrite rules. For example,
consider the plan \([\text{forward,left}]\), which implies that the robot must arrive at an intersection with a left turn. This plan can be rewritten as \([\text{forward,\square, left}]\) to indicate that it needs to populate a plan step with an action that specifies the intersection type at which it will make the left turn. These rewrite rules are repeatedly applied to the plan until it no longer contains any invalid action sequences. Table II shows the complete list of plan rewrite rules.

3) Dialogue: The goal of HOLD_CONVERSATION is to construct a complete plan, with no unfilled steps. If the plan is not complete, a query is generated and posed to the person for the first unfilled step in the plan. Information is extracted from the person’s response to fill the corresponding unfilled step in the plan. The type of the query depends on the pattern in which the unfilled step occurs. There are two query types: single, which requests a single piece of information, and open-ended, which gives the person more freedom in their response. Table III illustrates the different queries for each pattern and query-type.

If the query-type is single, HOLD_CONVERSATION looks for the presence of that particular type of information in the response. After finding it, all words up to it are removed and the remaining text is parsed in an open-ended fashion. Consider an example:

Robot: Which direction do I start out going?
Person: you start left, then turn right at the end of the hallway

Our parsing method extracts ‘left’ as the answer to the query and then replaces the corresponding \(\square\) in the plan with left. Then it parses ‘then turn right at the end of the hallway’ in an open-ended manner and inserts the extracted instructions into the plan after left. If the query-type is open-ended, the response is parsed in the same way as the response to the robot’s first question. The robot repeatedly poses questions, processes the respond, and applies rewrite rules until it generates a complete plan with no missing information. A complete and consistent plan indicates success and results in a transition to the FOLLOW_DIRECTIONS state.

If the plan is complete but not consistent, or if no plan could be constructed, then the plan \([\text{right, person}]\) is created and a transition to the FOLLOW_DIRECTIONS state is made. This
short plan causes the robot to rotate away from the person so that they are no longer in the field of view and will not be readdressed as an approachable person. After rotating 90° to the right, the robot transitions to the WANDER state and will seek out a new person to ask for directions.

4) Addressing Corner Cases: To help facilitate a more natural conversation, we have a small amount of code to address a few corner cases that may arise in spoken conversation. If a response to a query is not heard within 5 s, the robot states this fact and repeats its query. If the robot is not able to extract any useful information from a response, it indicates such and may provide some information about what it does understand (e.g., directions and intersections). If the robot goes two turns without the plan changing (e.g., it fails to understand the person’s instructions or it hears no response), the robot ends the conversation and carries out whatever portion of the plan has been achieved before. If the person indicated the robot misunderstood their last utterance, the robot backs up one step, using the previous iteration of the plan and its corresponding query. If the person indicates that they would like to start over, the robot resets the plan and asks its original query. Some sample conversations from our trials are shown in Table IV.

D. FOLLOW_DIRECTIONS

With a successfully extracted plan, the robot enters the FOLLOW_DIRECTIONS state. The plan includes direction, intersection, and goal actions. Direction and intersection actions are grounded in the environment by the navigation process described in Section II-C. The goal action is a transition condition to FOLLOW_DIRECTIONS that it has completed the plan provided by the person and should transition to the next state.

1) Plan Preprocessing: In Section III-A1, we described the DRIVE_THROUGH_INTERSECTION substate and its purpose in ensuring the robot exited the registered intersection before being able to detect another registered intersection and re-evaluate what to do. That behavior is important to FOLLOW_DIRECTIONS as well for a similar reason: if the robot entered a registered intersection, rotated in the direction specified in the plan, and immediately began looking for the subsequent intersection, it could mistakenly think it had reached it, despite still being in the same registered intersection. We want the robot to completely exit the current registered intersection before beginning to look for the subsequent one. To facilitate this behavior, FOLLOW_DIRECTIONS takes the plan received from HOLD_CONVERSATION, searches for all but the last instance of the pattern [int, dir], and inserts the following two actions after the direction action: [forward-through-int, forward]. As an example, the plan [forward, elbow, left, elbow, left, goal-F] would become

[forward, elbow, left, forward-through-int, forward, elbow, left, goal-F].

2) FOLLOW_DIRECTIONS Substates: The FOLLOW_DIRECTIONS state has five substates: a) MAKE_DECISION, b) DRIVE_FORWARD, c) ROTATE, d) DRIVE_THROUGH_INTERSECTION, and e) COMPLETE. FOLLOW_DIRECTIONS maintains a step counter, indicating the current step to execute. It enters the MAKE_DECISION substate first, initializing the step counter to the first step in the plan. When the current action is forward, it will enter the DRIVE_FORWARD substate wherein it drives forward until the subsequent intersection in the plan is found. In the example [forward, elbow, left, ...] the robot would drive forward until it detects an elbow intersection. As noted in Table I, some of the intersection keywords are less specific and only contain an indication of what hallway trajectories one would expect to find at the specified intersection. For

| Pattern | Query-type | Query |
|---------|------------|-------|
| int ... | open-ended | Could you tell me how to navigate to ⟨destination⟩? |
| goal ... | single | “Which direction do I start out going?” |
| turn-around dir ... | open-ended | “What do I do after turning around?” |
| ... left ... left ... | open-ended | “What do I do after I turn left (this being the ⟨nth⟩ left I take)?” |
| ... right ... right ... | open-ended | “What do I do after I turn right (this being the ⟨nth⟩ right I take)?” |
| ... elbow dir ... | open-ended | “Where do I go after the elbow (this being the ⟨jth⟩ elbow)?” |
| ... int forward dir ... | open-ended | “What do I do after going through the ⟨jth⟩ int?” |
| ... int ... | open-ended | “What do I do after getting to the ⟨jth⟩ int?” |
| ... int1 □ int2 ... | single | “When I am at ⟨int1⟩, which direction will I go to get to ⟨int2⟩?” |

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TABLE III: Query templates for plan patterns. The notation ⟨nth⟩ refers to a direction determiner generated based on how many direction actions of the same type appear prior to dir in the current partial plan. The notation ⟨jth⟩ refers to an intersection determiner generated based on how many intersection actions of the same type appear prior to int in the current partial plan. The first matching template applies when the current partial plan. The notation ⟨nth⟩ refers to a direction determiner generated based on how many direction actions of the same type appear prior to dir in the current partial plan. The notation ⟨jth⟩ refers to an intersection determiner generated based on how many intersection actions of the same type appear prior to int in the current partial plan. The first matching template applies when the current partial plan.

| Pattern | Query-type | Query |
|---------|------------|-------|
| int ... | open-ended | Could you tell me how to navigate to ⟨destination⟩? |
| goal ... | single | “Which direction do I start out going?” |
| turn-around dir ... | open-ended | “What do I do after turning around?” |
| ... left ... left ... | open-ended | “What do I do after I turn left (this being the ⟨nth⟩ left I take)?” |
| ... right ... right ... | open-ended | “What do I do after I turn right (this being the ⟨nth⟩ right I take)?” |
| ... elbow dir ... | open-ended | “Where do I go after the elbow (this being the ⟨jth⟩ elbow)?” |
| ... int forward dir ... | open-ended | “What do I do after going through the ⟨jth⟩ int?” |
| ... int ... | open-ended | “What do I do after getting to the ⟨jth⟩ int?” |
| ... int1 □ int2 ... | single | “When I am at ⟨int1⟩, which direction will I go to get to ⟨int2⟩?” |

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TABLE IV: Sample conversations from our trials.

| Speaker | Utterance |
|---------|----------|
| Robot: | Could you tell me how to navigate to 345? |
| Person: | yeah, turn around go to the end of the hall and you’ll take a lot to the bathroom. |
| Robot: | What do I do after getting to the first end of the hall? |
| Person: | you take a left at the bath. |
| Robot: | What do I do after I turn left? |
| Person: | app |
| Robot: | I did not understand that. What do I do after I turn left? |
| Person: | you go to the end of the hall. |
| Robot: | What do I do after getting to the second end of the hall? |
| Person: | turn right. |
| Robot: | What do I do after I turn right? |
| Person: | it’ll be the third door on the left. |
| Robot: | Thanks for your help. Have a great day! |

| Plan: | [turn-around, forward, end, left, end, right, goal-L] |
| Robot: | Could you tell me how to navigate to 276? |
| Person: | yeah, turn around then turn right then your first left and then the door will be on your left. |
| Robot: | Thanks for your help. Have a great day! |

| Plan: | [turn-around, forward, int-R, right, int-L, left, goal-L] |
| Robot: | Could you tell me how to navigate to 1273? |
| Person: | yes, turn right. |
| Robot: | What do I do after I turn right? |
| Person: | I did not hear you. What do I do after I turn right? |
| Person: | and then turn right. |
| Robot: | What do I do after I turn right (this being the second right I take)? |
| Person: | find room 1273. |
| Robot: | Thanks for your help. Have a great day! |

| Plan: | [forward, int-R, right, int-R, right, goal-F] |
example, int-L would specify a registered intersection of any type that includes a hallway trajectory labeled with the qualitative direction left.

Once the specified intersection has been detected, the robot will return to the MAKE_DECISION substate to determine what it needs to do next. It the next step in the plan contains a direction action that requires rotation (i.e., left, right, or turn-around), the robot will enter the ROTATE substate. In this substate, the robot will rotate in-place by a specified amount according to the direction specified in the plan: left $\rightarrow 90^\circ$, right $\rightarrow -90^\circ$, and turn-around $\rightarrow 180^\circ$. After rotating, the robot will return to the MAKE_DECISION substate. If the subsequent step is forward-through-int, the robot enters the DRIVE_THROUGH_INTERSECTION substate. As before, it requires that the intersection type change and the robot travel at least 2 m from where it rotated before it exits this substate and returns to the MAKE_DECISION substate.

Before each of the substates DRIVE_FORWARD, ROTATE, and DRIVE_THROUGH_INTERSECTION finish performing their task and return to the MAKE_DECISION substate, they increment the step counter accordingly. Eventually, the step counter will reach the goal action. When this occurs, MAKE_DECISION transitions to the COMPLETE substate. This is indicative of FOLLOW DIRECTIONS having successfully executed the plan and the robot will transition to the next state. When the goal action is goal-F, goal-L, or goal-R, the robot has reached the same hallway as the goal and must look for it. Thus the robot will transition to the NAVIGATE_DOOR state. When the goal action is person, the robot has carried out as many steps as the previous person was able to provide and must now seek out a new person to ask for instructions. Thus the robot will transition to the WANDER state. A diagram of this FSM is shown in Figure 5b.

3) Forward Driving Goals: When approaching a person, the robot may have moved to one side of the hallway and be in a suboptimal pose (similar to that described in Section III-A2). Additionally, because the conversation will have taken some amount of time, the person may have materialized as an obstacle in the quantitative map, directly in front of the robot. When the first action in the plan is forward, the robot may be unable to do so, even when using the technique described in Section III-A2, where we search with increasingly wider cone angles in the hopes of finding a median drivable trajectory. If no drivable trajectories are available from the robot’s pose (which is often the case because of the robot’s proximity to the person), we repeat the same search for a median drivable trajectory, but use positions that are horizontal to the robot’s pose. Starting at the robot’s current pose, we incrementally search left then right at distances of $\pm 0.5$ m, $\pm 1$ m, and $\pm 1.5$ m, with the expectation that at some horizontal position, we will be far enough away from the person to find a median drivable trajectory. We then use this median drivable trajectory as our forward driving goal. This helps to move us around the person and drive in the direction indicated. Note that this mechanism, also present in the WANDER state, is the one we alluded to in Section III-A2. Figure 9 provides a visual explanation of this process.

While in the DRIVE_FORWARD substate, the robot will continue driving forward until it either detects the intersection specified in the plan or reaches the end of the hallway. If it reaches the end of the hallway without detecting the desired intersection, the robot will perform a single 360$^\circ$ spin to ensure that it truly is at a dead-end. If, after performing this spin, it has not detected the specified intersection, it indicates failure to carry out the plan and will return to the WANDER state.

E. NAVIGATE_DOOR

Once the robot completes execution of the plan with a goal other than person, it will be located in the hallway containing the desired door and transitions to the NAVIGATE_DOOR state to conduct a systematic search to find the door. The search procedure depends on accurate door localization and common-sense reasoning. We leverage several key characteristics of our environment: doors are all of a similar shape, each door has a door tag displaying the room number, and room numbers are consecutive odd on one side of the hallway and consecutive even on the other. This lets the robot inspect the doors in a logical fashion.

To detect doors, doorways, and elevators, we rely on four standard pieces of sensor information from the robot: a) the camera image, b) the raw LiDAR data, c) the quantitative map, and d) the robot pose. We use the LiDAR data to first determine regions in the image that can contain doors, then search these regions for door proposals, and ultimately assign a confidence score to each proposal. Because the LiDAR data provides information about obstacle distance relative to the robot, we can use the robot’s position in the quantitative map to compute absolute locations for the door proposals.

1) Detecting Walls: We rely on 3D information from the LiDAR data to determine the walls. This data is represented as a collection of 2D $(x, y)$ coordinates that represent the location of obstacles in the environment surrounding the robot. An illustration of such data can be seen in Figure 10a. We apply
the Douglas-Peucker algorithm [11] to reduce the number of these points and establish line segments that can correspond to walls in the environment. We define each line segment as the 4-tuple \( (x_1, y_1, x_2, y_2) \) where \((x_1, y_1)\) and \((x_2, y_2)\) correspond to a pair of endpoints. The resulting line segments can be seen in Figure 10b. Due to occlusion or recession, this algorithm can produce disjoint line segments that correspond to the same wall. We employ two stages of clustering to merge these disjoint line segments into \textit{walls}.

Because line segments that correspond to the same wall must share the same orientation, we cluster the line segments with hierarchical clustering based on their angles. We refer to these clusters as \textit{orientation clusters}. To disambiguate line segments belonging to parallel but distinct walls, we perform a second stage of clustering. For each line segment within an orientation cluster, we rotate it by the negative of its angle so that the resulting line segment is parallel to the \( x \)-axis in a standard Cartesian coordinate system. The transformation is shown in Equation 1.

\[
\begin{bmatrix}
  x'_1 \\
  y'_1 \\
  x'_2 \\
  y'_2
\end{bmatrix} = \begin{bmatrix}
  \cos \theta & -\sin \theta \\
  \sin \theta & \cos \theta
\end{bmatrix} \begin{bmatrix}
  x_1 \\
  y_1 \\
  x_2 \\
  y_2
\end{bmatrix}
\]  

Equation 1

Now, for each resulting line segment \((x'_1, y'_1, x'_2, y'_2)\), its distance to the \( x \)-axis is equal to \( y'_1 (= y'_2) \). Thus, we cluster all of these line segments based on this distance to distinguish between parallel walls. At the end of this step, our final clusters consist of line segments that belong to the same wall. For each of these clusters, we merge all of the line segments into a single line segment \((\hat{x}_1, \hat{y}_1, \hat{x}_2, \hat{y}_2)\) by taking the two most extreme endpoints of the line segments. Each of these merged line segments represents a wall in the robot’s immediate environment. The final result can be seen in Figure 10c.

Now that we have the locations of the walls, we can create regions in the image that could contain doors. Because most doors, doorways, and elevators have a standard height of 2.2 m, we desire regions that are bounded above by this height and below by the ground level, 0 m. Knowing the camera intrinsics, \(K\), and extrinsics, \(R\) and \(t\), we can apply the transformation in Equation 2 to project the wall line segments onto the image at these height levels by setting \(h\) appropriately.

\[
\begin{bmatrix}
  u_1 \\
  v_1 \\
  u_2 \\
  v_2
\end{bmatrix} = K \begin{bmatrix}
  R & t
\end{bmatrix} \begin{bmatrix}
  \hat{x}_1 \\
  \hat{y}_1 \\
  \hat{x}_2 \\
  \hat{y}_2
\end{bmatrix}
\]  

Equation 2

Because we take real data from a moving robot as input, this projection might not always result in accurate pixel coordinates, which can cause complications when we search for edges that correspond to the tops of doors. Therefore, we incorporate a vertical distance tolerance of \( \pm 15 \) cm for the top boundary. A visualization of the boundaries and their tolerances can be seen in Figure 11. Each pair of a top and bottom boundary is considered as a distinct wall region.

2) \textit{Generating Door Proposals}: We use edge detection as a basis for generating door proposals, incorporating mechanisms that are robust to noisy edge detections which are prevalent in images obtained from a moving robot. We employ LSD (Line Segment Detector) to detect line segments in the image without any parameter tuning. Each line segment is represented as the 4-tuple \((u_1, v_1, u_2, v_2)\). Inspired by Shi and Samarabandu [27], we quantize the line segments into several bins depending on their orientation. We do this to isolate the line segments that can potentially belong to a door, specifically the two posts

![Image](image-url)
and the top. Therefore, we keep any vertical line segments as possible door posts. Then, we separate any lines in the top half of the image into three bins based on whether the line segment has a positive slope, negative slope, or a slope close to zero, respectively. An example result is shown in Figure 12.

Given the detected edges and the projected wall regions, we can search for possible doors in the environment. We iterate over each wall region to find doors in that region. First, any line segments, of any orientation, that lie outside of the horizontal range defined by the wall region are removed from consideration. Then, we iterate over pairs of vertical lines to generate door proposals. However, we only consider lines that are within a certain distance range of each other, approximately equivalent to the width of doors. We approximately localize the vertical lines in 3D space by projecting the raw LiDAR data to image coordinates, by Equation 2, and then computing the closest LiDAR point to each vertical line. That LiDAR point’s 3D location is used as the approximate location for the corresponding vertical line. Then we cluster the vertical lines based on their 3D locations to create a reduced set of possible door posts represented as \((u'_1, v'_1, u'_2, v'_2)\). Because \(u_1 = u_2\) for vertical lines, we compute the average \(u_1\) within a cluster to compute \(v'_1\) and \(v'_2\). Then we use \(v'_1\) to find \(v'_1\) and \(v'_2\) by computing the corresponding points on the top and bottom boundaries of the wall region, respectively. This creates a smaller set of lines that extend from the bottom boundary to the top boundary in the wall region on the image. Using these 3D locations of the lines in this reduced set, we compute a pairwise distance between them and only keep pairs whose distance is within the range \([0.5 \text{ m}, 1.25 \text{ m}]\).

3) Scoring proposals: We introduce a metric to determine how confident we are that a given pair of vertical lines corresponds to a door or elevator as some proposals could correspond to signs, posters, or wall structures. Akin to Del Pero et al. [10], we measure how much each proposal explains, or covers, the detected line segments in the image by computing the coverage of the vertical lines and top bar (the segment connecting the top points of the vertical lines) of the proposal. Multiple line segments may correspond to the same component of the door proposal, but could be disjoint and/or overlap due to noise or occlusion. First, we isolate the detected line segments that could correspond to the top of the door, by only retaining segments whose orientation matches the orientation of the top boundary of the wall region as well as lie within the top boundary’s vertical tolerance. Then, using the same approach as for the vertical lines, we compute the approximate 3D location for each endpoint of each of the remaining line segments, and only consider line segments whose endpoints are within the horizontal range: 0.15 m left of the left vertical line and 0.15 m right of the right vertical line.

With these remaining segments, we can compute what fraction, \(c_{\text{top}}\), they cover of the top horizontal area between the two vertical line segments. We take the same approach to the vertical line segments themselves. For each of the two vertical line segments, we find all of the original line segments that are within 0.2 m and compute how much they cover those line segments vertically, resulting in \(c_{\text{left}}\) and \(c_{\text{right}}\). These three values are aggregated to compute a score for each door as indicated in Equation 3.

\[
\text{score} = \frac{c_{\text{left}} + c_{\text{right}} + c_{\text{top}}}{3}
\]

Rather than have binary decisions about whether or not a proposal is a door, a confidence score can allow an online system to be adjusted to a desired false-positive rate. In our system, we use a confidence score threshold of 0.75, only considering detections with a score greater than or equal to this.

4) Localizing detections: Using the 3D locations of the door posts, we describe the location of the door as the tuple \(d = (x_{\text{min}}, y_{\text{min}}, x_{\text{max}}, y_{\text{max}})\) where \(\text{min}\) and \(\text{max}\) correspond to the closer and further door posts respectively. This allows for driving to both sides of the door as the door tag might be on either side. Because this process is performed in an online fashion on continuous image frames received from the camera, the same door can be detected multiple times at different time steps. Therefore, detections from different time steps are hierarchically clustered by the Euclidean distances between their center locations. For accurate clustering, we rely on additional information from the LiDAR data to accurately cluster door detections. For each door bounding box, we find all the 3D points whose corresponding pixel coordinates are within its bounds. We then take the median of these 3D points as the door detection’s center location. This allows for computing accurate door coordinates and filtering out false positives for driving-goal generation.

5) Driving-Goal Generation: For each of the resulting clusters, we compute the average locations of the door posts to create the final driving goals for that door. Only clusters whose size is \(>3\) are considered. These clusters are classified as being on the right side of the hallway or the left side based on a comparison between the robot’s trajectory down the hallway and the door locations (relative to the beginning of the hallway). Within these classifications, the clusters are sorted by increasing distance relative to the beginning of the hallway. This allows for driving to a specific door. For example, driving to the third door on the left can be achieved by retrieving the
coordinates of the door whose index is two, by zero-indexing, among doors classified as being on the left side of the hallway. The robot uses the coordinates of the door posts to create two driving goals so that it can position itself appropriately to read the door tag. Figure 13 illustrates the two desired positions. The door’s angle $\theta = \tan^{-1} \frac{\text{max} - \text{min}}{\text{max} - \text{min}}$ is computed and used to determine a driving goal that is $1$ m perpendicular to the door and with a target orientation orientation matching that of the door. Upon arrival at this driving goal, the robot pans its camera in the direction of the door to read its door tag with Google’s Optical Character Recognition API.

6) Common-Sense Navigation: Generally, the robot will drive straight down the center of the hallway, using the forward command, and only drive up to a door once it is within $3$ m. This behavior results in a good view of doors up ahead. If the index and/or classification of the desired door is unknown, common-sense knowledge about room labeling in an office environment is leveraged to guess what they are, based on the first door tag that is read. This can enable potentially more efficient goal-finding than exhaustive search alone. This common-sense knowledge is based on assumptions about doors being labeled in increasing or decreasing order, both numerically and alphabetically (in the case of a letter suffix), and even and odd doors being on different sides of the hallway. Given the door tag of the first door the robot inspects, it will use parity to determine what side the goal door is on. If the goal door is on the same side, it will compute the expected index of the goal door and drive down the hallway until it detects that door. Otherwise, it will start with the first door on the other side of the hallway. For example, if the desired door is room 335 and the first door tag read is 331, then room 335 will be two doors down on the same side of the hallway. Alternatively, if the first door tag is 330, only doors on the other side of the hallway will be inspected.

A number of mechanisms are incorporated to allow the robot to find the goal door in spite of any of these assumptions being invalidated. Firstly, at any given point, all the door tags read so far are used to determine whether or not the goal door was missed. This is done using the range and trend (whether they are increasing or decreasing) of the door values to check whether the robot should have come across the door in its path. If the door has not been missed, the robot will continue to inspect doors on the current side of the hallway until it reaches the end of the hallway. In both of these cases, the robot returns to the start of the hallway and begins an exhaustive search of all doors in the hallway to find the goal door. If the robot still has not found the goal door after this exhaustive search, it returns to the WANDER state.

### IV. System Evaluation

Our system design was developed and validated in three buildings (EE, MSEE, and PHYS). In order to evaluate the generalizability and robustness of our system’s performance, we performed 52 trials in 4 distinct floors in each of three new buildings (HAMP, KNOY, and ME) it had not been deployed in before. With three exceptions described below, we froze our software after development before the evaluation trials. For these trials, we recruited 13 volunteers to provide directions to the robot. These volunteers were untrained users who had never interacted with the robot before nor were aware of what it understood or was capable of. Each volunteer assisted with 1–6 trials.

#### A. Experimental Setup

For each trial, the robot was placed on a floor of one of the three new buildings and given a random door number as the goal. The volunteer was instructed to stand in a location where the robot would be allowed to WANDER for some time before seeing them. If the robot re-entered the WANDER state at any point in the trial, the volunteer was instructed to relocate to a position that the robot would come across after being allowed to wander for some time. A trial was considered a complete success if the robot reached the correct goal door and read its door tag. A trial was concluded and subsequently declared a failure if the robot did not reach the goal after several attempts. In some trials, some minor manual intervention was used to partially rotate the robot or prevent it from crashing into a wall to allow the trial to continue.

#### B. Trial Results

The number of successful trials is shown in Table Va on a per-building basis. Overall, the system was able to successfully reach the given goal in 76.9% of the trials. Of the 12 floor plans tested, the robot was able to successfully find the goal at least twice on every floor and usually three or more times (8/12 floors). This result highlights the ability of our system to generalize to new floor plans.

One of the characteristics of our system is its ability to recover from individual behavior failures. Of the 52 trials, only $3 \ (\approx 5.7\%)$ succeeded without any behavior failures. When failures do occur, either from shortcomings of the individual behaviors or incorrect instructions from volunteers, the robot is able to recover and make multiple attempts at its task. Table Vb shows the success rate of each behavior. Despite there being multiple instances of each behavior due to failure, the robot is ultimately able to reach the goal door with the subsequent recovery from the individual behavior failures.

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3Our original intent was to not have any volunteers but instead to have the WANDER state find people naturally occurring in the environment to model real visitors soliciting help in finding their way from locals. COVID-19 prevented us from doing this.

4An online appendix at https://github.com/qobi/amazing-race contains the floor plan of each building and describes each trial in detail, including the building, floor, volunteer, goal, a transcript of the dialog, the plan extracted, the map constructed with the route taken, indication of success or failure, and a description of the failure reason upon failure. The appendix also includes three videos depicting three complete trials, one in each building.
This ability effectively increased the success rate by a factor of 13.3.

C. Observations and Improvements

As the trials were conducted, many observations were made about each behavior’s interaction with the complex environments in which the robot was evaluated. Although the system recovers from most individual behavior failures, reducing the number of these would lead to faster and more efficient goal finding. In this section, we discuss these observations and how they can potentially be used as points of improvement in future work.

1) **APPROACH_PERSON**: We observed several challenges associated with successfully and safely navigating to a person to ask them for directions. YOLOv3 cannot distinguish between people and pictures of people on the walls. In some trials, this led to the robot repeatedly driving up to walls containing pictures of people and attempting to initiate **HOLD_CONVERSATION**. Potential solutions include using body size as a prior to determine whether the detected person has the correct size for the detected distance or incorporating body-pose estimation to help make the distinction. Also, constraints can be applied to the locations of person detections, such as having to touch the ground, to eliminate detections of people on posters and signs from consideration.

Another point of difficulty was detecting and localizing people that are far away. People that are small in the camera’s field of view are more difficult to detect. Even if they are detected, the bounding boxes are small, thus having fewer corresponding 3D LiDAR points, making it difficult to localize, track, and classify person tracks accurately. Similar, consistent, accurate localization of people was also difficult when they were occluded by objects such as drinking fountains or trash cans, or when they were positioned close to a wall. These objects would often overlap with the person detections, which would affect the localization of the person themselves as some 3D LiDAR points overlapping the box would actually correspond to the object or wall instead of the person. These issues created tracks that would rapidly switch between being approachable and not approachable, which caused the system to correspondingly switch between WANDER and **APPROACH_PERSON** rapidly. This explains the high number of instances of WANDER and **APPROACH_PERSON** on a per-trial basis as well as the low success rate of **APPROACH_PERSON**. The robot would eventually reach the person, but would sometimes do so in an inefficient manner.

2) **HOLD_CONVERSATION**: The most common observation made when volunteers were providing instructions to the robot was their use of terminology and hand gestures that the robot did not understand. Some volunteers tried to describe directions using gestures, distances, angles, and objects. Future work includes developing a more generalizable and robust conversation engine that is capable of handling the diversity possible in a set of navigation instructions. Additionally, the plan structure could also be expanded to include distances, angles, objects, landmarks, text, arrows, and signs. Many of those have multiple modalities that could also be explored; e.g., distances could be measured in feet, meters, steps, or time, i.e., ‘walk that way for about 2 minutes.’

Aside from this, there was one trial where Google’s Speech-to-Text API returned a non-ASCII character (°), which was not supported by our message passing, and caused our **HOLD_CONVERSATION** behavior to die. We manually restarted the **HOLD_CONVERSATION** behavior and the trial continued to success.

3) **FOLLOW_DIRECTIONS**: Many of the building floors featured complexities not seen during development, such as open spaces and variation in both hallway width and turn angles. In particular, one building had hallways that branched off at 45° angles. This caused some confusion both in processing and executing the navigation instructions provided by the person. Some people would indicate that the robot should drive ‘straight’ when it got to those intersections while others indicated the robot should ‘turn.’ When told to drive ‘straight,’ **FOLLOW_DIRECTIONS** would detect that it could no longer drive **forward** after reaching the end of the hallway where the hallway would veer off at 45° and thus indicate failure. When told to turn ‘left,’ **FOLLOW_DIRECTIONS** would not detect the left turn and also indicate failure. An area of future research includes developing adaptive methods for determining novel intersection types in new indoor environments.

In a different building, the robot could not detect a particular narrow hallway opening (≈1.5 m wide when most hallways were 2-4 m wide) due to a hyperparameter corresponding to the hallway width. We adjusted it accordingly after the first 4 trials, and left it unchanged for the remainder of the trials. Dynamically detecting characteristics like this in novel environments is an area of future research.

Finally, as the robot is driving around, it is building a quantitative map in real-time and relies on map updates to determine where there are registered intersections. When the conjoining hallways are narrow, the robot sometimes does not have enough data from its LiDAR to have built a reliable-enough quantitative map to detect the intersection correctly. Instead of detecting the intersection, the robot drives past it unaware. Planned future work includes using a neural network

### TABLE V: Results.

| (a) Trial results. | (b) Behavior success rate. |
|--------------------|---------------------------|
| Building | Successes | Total | Success rate | Behavior | Total Instances | Average instances per trial | Success rate |
| HAMP  | 11 | 17 | 64.7% | WANDER | 390 | 7.5 | 0.39 |
| KNOY  | 13 | 16 | 81.3% | APPROACH_PERSON | 385 | 7.4 | 0.47 |
| ME  | 16 | 19 | 84.2% | HOLD_CONVERSATION | 183 | 3.5 | 0.86 |
| all  | 40 | 52 | 76.9% | FOLLOW_DIRECTIONS | 182 | 3.5 | 0.68 |
|      |      |      |       | NAVIGATE_DOOR | 99 | 1.9 | 0.40 |
to improve the detection of intersections and execution of the \texttt{FollowDirections} behavior in spite of an incomplete map.

4) \texttt{NavigateDoor}: The \texttt{NavigateDoor} behavior exhibited difficulty in finding the goal door in some situations. First, many doors were occluded or only partially visible in the robot’s field of view and the door detection method does not support detecting doors in these scenarios. A point for future work could be to train a neural-network-based object detector to robustly detect doors in spite of occlusion. Additionally, the network could be trained to detect other objects as well to enable the robot to find something beyond a room.

Another observation is that although the common-sense reasoning led the robot to efficiently find the goal in some trials, in many cases, it was disrupted by both missed and false-positive door detections. In these scenarios, the \texttt{NavigateDoor} behavior resorted to exhaustive search to find the goal door and was typically able to locate it. However, on a larger scale, exhaustive search would be impractical so a more robust reasoning and navigation system is an area of future work. To help remedy missed doors, we adjusted the threshold for the hierarchical clustering of door detections from 0.25 m to 0.5 m to create fewer but larger clusters. This parameter change was done after the first 7 trials and kept for the remaining trials.

We also found two issues involving using Google’s Optical Character Recognition (OCR) to read door tags. The first issue involved misreads, which happened twice in our trials. The robot drove up to the correct door, but read “goio” instead of “go10.” The same thing occurred with “go55” being misread as “go55.” A simple string replacement for commonly mistaken characters/digits would solve this problem (e.g., o ⇒ 0, i ⇒ 1, S ⇒ 5, etc.). The other challenge with OCR was distinguishing any text read from text read from the door tags. In one failed trial, the robot drove up to a door and read an advertisement about an event occurring in a particular room. The room it was referring to was our goal room (which happened to be about 2 m away, across the hall). In another failed trial, the robot failed to detect the goal door, drove up to the subsequent door, but still read the goal door’s door tag. In both of these cases, the robot erroneously claimed success. Being able to distinguish between a door tag and other signage or text, as well as being able to assign a single door tag to a single door, would alleviate this issue. We counted the two trials with OCR misreads as successes (since the robot did successfully accomplish all of the behaviors leading up to finding the correct door) and counted the two trials with the advertisement and the adjacent door as the mistaken goal as failures.

Lastly, after the first 24 trials, we discovered an issue where the robot was not clearing its set of detected door locations in between different instances of the \texttt{NavigateDoor} behavior within the same trial. This was fixed for the remaining trials as the intention was to only reason about doors in the current hallway as that is where the goal should be located. However, in future work, retaining and reasoning about all detected doors could enable the robot to find the goal without directions as well as return to rooms it has already visited if given instructions to do so.

V. RELATED WORK

Several research groups have constructed a system that accomplishes a comprehensive task similar to ours. We first compare and contrast our system to these other comprehensive systems. Then, we compare our individual behaviors to other research that has focused on similar behavior-specific tasks.

A. Systems

In Table VI and Table VII, we compare our system to those of the following groups: Birmingham [15], whose task is to find an object within a small office environment; Munich [5], whose task is to navigate the streets of Munich and reach a downtown plaza; UMBC [21], whose task is to follow natural-language directions to an office on a building floor; and Cornell [22], whose task is to follow a natural-language directive (in a specified grammar) to an outdoor goal location.

All five groups perform their task in the real world. Our results, along with Birmingham and Cornell, are based on a large number of trials, which helps to support the success rate reported. Our success rate is comparable to the other groups, but, as we will show in the subsequent tables, we also take on more challenges.

Table VIIa describes the test environment and how many distinct environments each group tested on. We test in 12 distinct environments, which is much larger than any other group. Having multiple trials in a large number of distinct environments provides some additional support to the generalizability of our system. We also stress that our 12 environments are distinct from the environments we trained on and developed for. Doing so prevents us from “training on (or developing for) the test set,” which carries the risk of overfitting to a particular environment and biasing the generalizability of a system’s performance. Like most of the other systems, we operate in an unknown environment, without a map.

Table VIIb compares how the robot interacts with people and gets directions. Unlike UMBC and Cornell, which have a single set of directions provided to the robot at the beginning of the trial, we have to find people in our environment that we can ask for directions. These people are untrained and unfamiliar with what the robot understands or is capable of. Along with Birmingham, we allow for open-ended conversation, which increases the diversity of responses. Finally, our conversation takes place via spoken dialogue which no other systems do. (Munich uses a GUI to get responses, while Birmingham uses text input.) These differences make our task considerably harder than those of other systems.

Finally, in Table VIIc, we point out a few additional ways in which our task sets us apart from the other systems. Our robot...
TABLE VII: Comparison with Related Work.

(a) Test environment.

| group       | # of test environments | test environment                        | train/test environments are different | map provided |
|-------------|------------------------|------------------------------------------|--------------------------------------|--------------|
| ours        | 12                     | floor of building                        | yes                                  | no           |
| Birmingham  | 1                      | 11 m² with hallway, 2 offices, and 1 conference room | unspecified                          | no           |
| Munich      | 1                      | downtown Munich                          | unspecified                          | no           |
| UMBC        | 1                      | floor of building                        | yes                                  | yes          |
| Cornell     | 1                      | 1 km² outdoor facility with 12 buildings | unspecified                          | no           |

(b) People interaction and direction-giving.

| group       | interacts with live people | untrained people | multi-turn conversation | open-ended conversation | spoken dialogue |
|-------------|-----------------------------|------------------|--------------------------|-------------------------|-----------------|
| ours        | yes                         | yes              | yes                      | yes                     | yes             |
| Birmingham  | yes                         | unspecified      | yes                      | yes                     | no              |
| Munich      | yes                         | yes              | no                       | yes                     | no              |
| UMBC        | no a                        | yes              | no                       | no                      | no              |
| Cornell     | no b                        | no               | no                       | no                      | no              |

*a* This paper takes, as the input to their trial, a single, open-ended text instruction from an untrained user.

*b* This paper takes, as the input to their trial, a single, open-ended text instruction from a predefined grammar called “TBS.”

(c) Directions, goals, and recovery.

| group       | follows directions | can detect when directions are wrong | robot detects goal independently | recovers from failure |
|-------------|--------------------|-------------------------------------|----------------------------------|-----------------------|
| ours        | yes                | yes                                 | yes                              | yes                   |
| Birmingham  | no                 | no                                  | unspecified                      | yes                   |
| Munich      | yes                | no                                  | unspecified                      | yes                   |
| UMBC        | yes                | yes                                 | unspecified                      | yes                   |
| Cornell     | yes                | no                                  | yes                              | no                    |

has to follow directions, rather than simply exploring until the goal is found. Exploring may work when the environment is small, but becomes intractable as the environment increases in size. When the directions it has are wrong, both our robot and UMBC’s are capable of detecting this. In UMBC’s case, they backtrack and recompute the next-most-likely path to the goal. In our case, we simply revert to WANDER and seek out another person to ask for directions. Our robot is capable of discovering and detecting the goal independently, while it is unclear whether all systems are capable of that ability. Lastly, like most other systems, we are able to recover from individual behavior failures and continue working towards the goal.

B. Behaviors

As described earlier, our system combines a number of behaviors, each of which solve one of the tasks presented by The Amazing Race™ challenge. The first is autonomous navigation in an indoor environment. Barrett et al. [3] employ a learning mechanism to acquire the semantics for direction keywords such as ‘left of,’ ‘right of,’ and ‘behind’ and then use these semantics for planning and describing robot paths. Because our focus was to design a complete system for navigation in an unknown environment, we predefined a similar set of directions for the WANDER and FOLLOW_DIRECTIONS state and used a novel method for determining whether they are available.

The next crucial task is to find a person and receive and interpret directions from them. The Jackrabbbot lab at Stanford has developed a robot that complies with social conventions such as understanding [26] and predicting [2] human trajectory in crowded scenes. When looking for and approaching people, our robot also complies with expected conventions such as determining which people are approachable, introducing itself as it approaches, and not invading personal space when having a conversation.

Bauer et al. [4, 5, 6] define a set of heuristic rules and a complex finite-state machine to obtain specific pieces of information from a person through a touch screen interface on their robot. Our system, however, takes full spoken natural-language utterances as input and extracts instructions from them. Oh et al. [22] and Boularias et al. [8] require a specific syntactic structure of natural-language commands called Tactical Behavior Specification to simplify the parsing problem. Our parsing method does not depend on such a strict grammar because it would be impractical for interacting with people unfamiliar with the robot. Kollar et al. [19] train a model to extract spatial-description clauses from natural-language directions to determine the corresponding path in the environment. Our method does not rely on training.

A single person’s response may have insufficient, vague, or incorrect information. Thomason et al. [30] present a dialogue system that can compensate for this issue by generating queries about missing pieces of information, specifically the action, patient, recipient, or some combination of them. Our dialogue system does not predefine what or how much information we seek and instead dynamically infers and generates queries for what information is missing.

In order to navigate in the environment, given the natural-language directions, the robot needs a semantic map of the environment. Hemachandra et al. [16] rely on AprilTag fiducials to classify regions in the environment for autonomous navigation. However, this prevents practical operation in any
unknown environment because it would have to be labeled with these fiducials. Sündehauf et al. [29] explore new areas and create a semantic map through the classification of sequences of image frames as places (e.g., office or kitchen). Pangercic et al. [24] create semantic object maps in a kitchen environment. They have a RGBD camera that enables their robot to perform fetch and place tasks. We use the occupancy grid, door detection, and text recognition to make a semantic map of an unknown environment.

Many approaches, including ours, rely on edge or line segment detection as a basis for finding door posts. Stoeter et al. [28] detects door frames by detecting vertical stripes in the image, but other objects or parts of the background could be responsible for vertical edges. More complex approaches look for edges in the image that form an upside-down U-shape to create door detections [18, 27]. These methods depend on high quality detected edges, which are not necessarily possible to obtain especially on images captured from a camera on a robot navigating in areas with varying, possibly poor, lighting conditions. Our method incorporates noise-tolerance mechanisms that simultaneously allow for door detection in spite of poor edge detection and measuring the confidence of those detections.

In the case of Shi and Samarabandu [27], only U-shapes that intersect the corridor lines are considered doors in order to avoid false positives caused by signs or posters. These corridor lines are obtained by finding the vanishing lines that have the most intersections with the bottoms of vertical lines. Olmschenk and Zhu [23] employ a similar method to finding corridor lines by detecting the vanishing point and vertical lines in an image to determine where the wall meets the floor. This approach is impractical for two reasons: a) walls orthogonal to the viewpoint are ignored and b) patterns in the image, such as floor tiling, can induce strong edge detections that can be confused for corridor lines. We incorporate 3D information from LiDAR data to reliably and generally detect wall regions and avoid this issue.

Hanheide et al. [15] employ a knowledge hierarchy that enables reasoning over known pieces of information in order to perform task planning, execution, and task-failure explanation. Because our robot has no prior knowledge about the environment, we extract information such as driving directions and door locations in an online fashion to execute navigation instructions and plan paths to potential locations of the goal.

We demonstrated that our system was successful in 76.9% of the trials that we conducted. As discussed, future work entails making improvements to each of the behaviors in our system to both improve the success rate and increase the scope of the task.

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