# Is Someone in this Office Available to Help Me?

# **Proactively Seeking Help from Spatially-Situated Humans**

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Abstract Robots are increasingly autonomous in our environments, but they still must overcome limited sensing, reasoning, and actuating capabilities while completing services for humans. While some work has focused on robots that proactively request help from humans to reduce their limitations, the work often assumes that humans are supervising the robot and always available to help. In this work, we instead investigate the feasibility of asking for help from humans in the environment who benefit from its services. Unlike other human helpers that constantly monitor a robot's progress, humans in the environment are not supervisors and a robot must proactively navigate to them to receive help. We contribute a study that shows that several of our environment occupants are willing to help our robot, but, as expected, they have constraints that limit their availability due to their own work schedules. Interestingly, the study further shows that an available human is not always in close proximity to the robot. We present an extended model that includes the availability of humans in the environment, and demonstrate how a navigation planner can incorporate this information to plan paths that increase the likelihood that a robot can find an available helper when it needs one. Finally, we discuss further opportunities for the robot to adapt and learn from the occupants over time.

**Keywords** Human–robot interaction • User study • Asking for help • Planning

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#### 1 Introduction

Robots are becoming increasingly able to perform services autonomously in our environments. They can give visitors directions in malls [35] and tours in museums [36], and act as companions for individual users [29]. Despite these great strides, robots are still not ubiquitous due to their sensing and actuation limitations that can affect their task performance. For example, many robots have difficulty recognizing speech in loud environments



or recognizing obstacles to avoid while navigating, and they may not have the physical ability to manipulate objects.

To overcome these limitations, some work has focused on reasoning about a robot's current state and proactively requesting humans to direct the robot's actions during tasks [2, 16, 29, 39]. However, there is always an assumption that humans are available to help a robot in any location, whether the help comes from supervisors who assign tasks and have incentive for it to perform [2, 16], or from bystanders who do not benefit from the robot's tasks [39]. Additionally, the work has been limited to asking for only one kind of help (e.g., localization) at a time.

In this work, we instead focus on asking for several types of localization and manipulation help from the actual occupants of the environment and beneficiaries of a robot's services. We argue that robots that ask for help from occupants combine the benefits of asking bystanders and supervisors in the following ways:

- Occupants should answer robots' questions during tasks for other occupants with the incentive that the help will be reciprocated during tasks for them.
- The burden of help is distributed among many occupants in the environment.

However, unlike supervisors and bystanders:

- Occupants are **not** always available to help the robot.
- Occupants are spatially-situated and cannot help the robot at every location in the environment.

We first review our building environment, robot, and its limitations and define several types of help that a robot could request from occupants to overcome those limitations. We, then, contribute a study that shows that, despite our busy office environment, several occupants are willing to help our robot with its limitations, but they have work constraints that limit their availability. Additionally, there are few available occupants in our environment (and likely in many environments) at any given time and a robot will have to proactively navigate to seek help if it needs it. Based on these findings, we contribute a model of an environment, robot, and occupants in it and demonstrate how a navigation planner can plan paths around available occupants' known locations to increase the likelihood that a robot can find help quickly when it needs it, rather than assuming there is always a human available. Finally, we discuss several qualitative results of our study which indicate the need for further extending the models of occupants.

#### 2 Related Work

Robots have limitations that affect their task performance. Human supervisors have traditionally been used to overcome a robot's limitations by monitoring robot progress and intervening when necessary, but such help can be very expensive in terms of monitoring time and cognitive load on the helper [40]. Much recent work has focused on different techniques to allow robots to reason about their own limitations and capabilities to proactively ask for help from supervisors, teachers, and bystanders in the environment. These different types of help have been classified in a variety of ways [17, 20, 26, 31], but we focus in particular on supervisors and bystanders and investigate a new classification of helpers—the inenvironment beneficiaries of robots' tasks (i.e., the robot users [23, 29]).

#### 2.1 Supervisors

Many different methods have been proposed for supervisors to help including providing assistance at different levels of granularity depending on the robot's capabilities [12] and participating in mixed-initiative interactions to ensure the robot performs its task effectively [33]. Initial work in robot learning required teacher supervisors to physically perform the task for the robot to imitate [19, 24, 28]. Since then, teachers have been able to accurately label data both when the robot requests it during tasks and through corrective feedback after tasks are performed in order for



robots to learn policies for which actions to take [2].

Two important assumptions are made in terms of robots employing help from supervisors: supervisors have **incentives** to respond and they participate in **long-term interactions** giving both robot and human chances to learn about each other.

Incentives It is assumed that teachers and supervisors have incentives to help their robots complete their tasks. They are either paid to monitor the robot's movements or they do so for research and teaching purposes that further the robot's knowledge. Additionally, while it is assumed that teachers will provide less feedback over time, they are still available to provide corrective feedback or wait for questions during the entire learning process. As a result, the robot does not need to take into account the number of times or frequency that it has needed help to determine whether it should ask for help at the present time. This is in contrast to other active learning methods which assume that there is a cost, such as time to respond or annoyance, associated with asking [1, 8, 27].

Long-Term Interaction Because supervision occurs over time, there are additional opportunities for robots to take advantage of the long-term interactions to model and learn about the human and vice versa. Supervisors are often assumed, with few exceptions (e.g., [16]), to have in-depth knowledge about how robots work so that they can help them appropriately. However, even without this assumption, robots with knowledge of supervisors should (1) take into account helper expertise to determine the type of question that the robot should ask [5, 15, 16], (2) ground or familiarize the helper with the robot's current state to increase the likelihood of accurate responses [7, 30], and (3) model the helper's interruptibility or availability to answer questions [14, 35].

While supervision ensures that a robot will always be able to find help from a trusted human helper, it is an expensive requirement that cannot be scaled as we continue to deploy more and more robots. To reduce the dependency on a single supervisor, it has recently been suggested

that bystanders in the environment can help a robot.

#### 2.2 Bystanders

The number of bystanders is assumed to be high compared to supervisors, distributing the burden of help across a large number of people [4, 21, 25, 39]. Robots can benefit from the **distributed help**, but the requirement of a crowded environment requires **spatial constraints** on where these robots can be deployed.

Distributed Help Human computation (e.g., [37, 38]) and crowd-sourcing (on websites like Amazon.com's Mechanical Turk) gather help from a distributed set of people. Crowd-sourcing has been used to label pictures [37] and translate audio [6, 34]. In robot domains, bystanders in busy environments have helped robots complete tasks in locations as varied as offices [4], conferences [25], and even on the street [39]. Because the number of people in these areas is so high, there is a very limited possibility that any particular person will be asked for help too frequently, limiting the annoyance and interruption of the requests for help.

Spatial Constraints Bystanders are more often found in crowded spaces, adding spatial constraints to the robot's deployment. While humans are not actively in contact with the robot all the time, there is still an assumption that at least **one** human will help the robot shortly after it requests it. Because these robots do not model humans in the environment in terms of who will be available or where they are located, nor do they proactively contact a known helper, they have little control over the help they receive and cannot plan to optimize their performance using that help. As a result, their performance is dependent on the crowds in the environment.

#### 2.3 Our Work

We argue that asking for help from occupants in the environment combines the benefits of



supervisors in terms of **incentives** to answer and **long-term interactions** and the benefits of bystanders to **distribute help** among many people. Additionally, seeking help from occupants in offices relaxes the **spatial constraints** of crowded areas but requires **proactive navigation** to find available occupants. We expect that because the office occupants are the beneficiaries of the robot's tasks, they will be likely to respond to requests for help to complete tasks. However, there has been little prior work focused on the opportunities for robots to ask for help from these occupants (e.g., users of the robot [23, 29]).

In this work, we first define the problem of seeking help from building occupants. Then, we review our environment, robot, and our robot's limitations that it requires human help with. We present a study to understand the willingness and availability of occupants to help a robot that performs services for them. We find that few people are willing to help at any given time, and in order for the robot to find these people during tasks, it will need to model where they are located and modify its navigational plans to move near them. We then contribute a model of the environment that includes not only the robot and its robot limitations, but also available humans and demonstrate that a robot can use this model to optimize its navigation for a task to increase the likelihood of finding an available occupant.

# 3 Seeking Help from Spatially-Situated Building Occupants

We define **occupants** of buildings as having predefined work spaces and conducting work which requires that they be present over a period of time. While occupants have similarities to both supervisors and bystanders, they also have constraints which violate the assumptions of previous work. In particular, they are spatially-situated in the environment so no single occupant can help a robot at every location. Additionally, the occupants are not necessarily monitoring a robot or their email, and may miss or be late to respond to electronic requests for help. As a result, a robot will need to navigate to an occupant's office to request help. It will also need to learn and model

each human's availability through long-term interaction to avoid navigating to empty offices or interrupting meetings in offices. We discuss each of the aspects of building occupants in turn and the research questions we address.

Distributed Help Because there are many occupants in a building, the burden of helping a robot is distributed among them. This is important because occupants are busy and may not be able to answer too frequently. However, it is unclear whether occupants are willing to help at all given that they have other work to do. This work will address the following questions related to occupant help:

- Are office occupants willing and available to help a robot perform its tasks?
- Are they willing to provide one type of help more than others (e.g., are they unwilling to help with tasks that require them to leave their office)?
- Are office occupants willing to help the robot even if they are busy in meetings or on the phone?

Incentives Because a robot would know occupants' office locations, it could provide services or incentives to encourage occupants to help it. If occupants want to continue to receive services and incentives from the robot (e.g., mail delivery), they must also agree to help the robot at some times. In this work, we aim to answer the following questions relating to incentives:

- Do office occupants report that they are motivated to answer questions with incentives?
- Do they actually answer more frequently when offered an incentive?

Long-Term Interaction Unlike bystanders who may only have to answer a particular robot's questions once, an office occupant will be asked questions more often including times that may cause interruptions to meetings and other work or other annoyances. However, unlike supervisors, there are possibly several helpers to choose from. Longterm interactions allow the robot to learn who is often available at certain times and preferences for when and what types of help they are willing



to answer. We address the following questions towards this interaction:

- Is there a novelty effect associated with willingness to help the robot and does willingness to help decrease over time?
- Can the availability of occupants be modeled to take into account who will be able to help?
- Does occupant availability change through the day and do we need to model this change?

Navigation Finally, due to the lack of constant supervision and asynchronicity of email, the robot must navigate to the spatially-situated occupants to determine their availability and to ask them for help if needed. Current navigational models have included multiple layers of costs of navigation around people, such as the uncertainty in the path and the path distance (e.g., [9, 13, 22]), but have not included costs of who along the path is available to help. Intuitively, a robot should choose short paths that also have humans available to

help it if necessary. We will answer the following question:

Can a robot use availability information to determine a path that increases its likelihood of finding help when it needs it?

Next, we will describe our robot and environment with office occupants that were used to answer these questions and to understand the feasibility of asking occupants for help with a variety of different robot limitations.

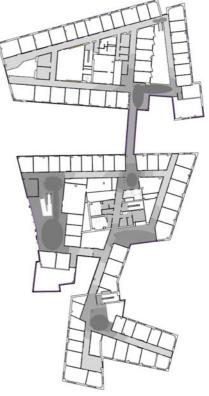
#### 4 Robot and Environment Domain

Our environment consists of one floor of an academic building containing 79 offices: 35 individual offices for faculty and administrators and 44 offices each shared by 2–3 graduate students. Our robot, CoBot (Fig. 1a), is capable of autonomous localization and navigation in the environment as

Fig. 1 a CoBot has manipulation limitations without arms and b has localization uncertainty in the hallways of the building (the darker the grey the more uncertainty in that location)



(a) The CoBot Robot



(b) Areas of Uncertainty



well as dialog with humans. It has a laptop with the screen facing backwards, away from the direction of movement, that occupants can use to interact with the robot while it performs tasks autonomously for them in the building.

However, like many robots today, CoBot has limitations. CoBot has high localization uncertainty in large open spaces (Fig. 1b—darker grey areas indicate more uncertainty) and also has difficulty perceiving chairs found in common areas resulting in increased navigation time as it attempts to re-localize or avoid these areas entirely. Additionally, CoBot does not have arms or the ability to manipulate objects to push chairs out of the way or pick up the mail to give to the building occupants. While the robot can overcome some of these challenges autonomously, inevitably, it must ask for help from humans sometimes to resolve each of these limitations.

In particular, we are interested in occupants' willingness to help the robot with these different limitations when the robot proactively navigates to their door to request the help. These requests

potentially take different amounts of time to answer and some require the occupant to leave their office to perform the requested help. The questions are all spoken out loud for the occupants to hear and displayed on the robot's laptop screen, but we require that the occupants answer the questions using the visual user interface on the laptop as it cannot understand speech.

### 4.1 Localization Help

When CoBot requires localization help, it can find an open door to ask the occupants to share their room number in the following way:

I cannot determine my location. What is the room number of this office? (multiple choice)

After speaking the question, CoBot lists three predictions of the possible office numbers and an additional textbox (in case the three office numbers were all incorrect) for the occupant to respond with. Because building occupants should



Fig. 2 Occupants were asked to answer a multiple choice localization question, move chairs out of the way, and write a note on another occupant's door



know their own office number, CoBot's localization questions should be fast for them to respond to and do not require the occupants to leave their offices except for accessing the robot's backwards facing screen (Fig. 2a).

### 4.2 Moving Chairs Help

Our building contains many seating areas with moveable chairs that are hard for the robot to detect. Even if CoBot could detect the chairs, it has no way of physically moving chairs that are blocking its path. CoBot navigated to occupants' offices and asked them to check and move chairs in the closest common area so that it could pass:

My laser range finder cannot determine the location of chair legs in the common area. Can you please move chairs in the common area to clear a path for me?

While occupants can easily identify and move chairs out of CoBot's way, this task requires that participants leave their offices to help the robot (Fig. 2b). Help with this limitation ensures that CoBot can safely navigate through the environment, assuming that the occupants actually move the chairs as requested. The occupants are asked to confirm their action on the laptop user interface so that the robot knows it is safe to continue.

#### 4.3 Writing Notes About Mail Delivery

In this work, we assume that CoBot will eventually perform a mail delivery task. CoBot does not have the manipulation abilities to select mail for an occupant or leave a message that a package is available. This limitation affects its ability to perform its task for occupants and therefore requires occupants to perform some of the robot's task for it. The robot requested that occupants write a note to notify a nearby occupant that they have a package waiting in the mailroom located one floor below our test floor (Fig. 2c):

I am trying to deliver a package to room 7505, but the door is closed. Can you please use the paper and pen in the bag on my left to write a note that a package is available downstairs and place it on their door?

We assume that the robot can find an office closeby to write the note. In this study, the office number of the nearby office (here 7505) changed depending on the occupants' location to ensure the occupants did not have to walk too far out of their office to deliver this message—the room was on average five offices away from a helper. When CoBot navigated to offices to request help writing a note, it carried paper and pens in a tote bag for the occupants to use.

### 5 Occupant Availability Study

In order to understand the feasibility of asking occupants for different types of help, we designed a study in which CoBot visited every office on one floor of our building to ask each type of question at different times of day. We measure the number of times each occupant is available in their office and willing to help for each question type as well as the amount of time they spend helping the robot. Because we were exploring the feasibility of asking different types of questions in this study and not testing the autonomy of the robot, CoBot was wizard-of-oz'd [18].

#### 5.1 Study Design and Procedure

Prior to the study, occupants on one floor of our academic building were told that the robot would soon be deployed in our environment to perform services for them, such as mail delivery. Additionally, they were told that it sometimes requires help to overcome its limitations, and that we were currently testing the robot's ability to ask for and receive help. Occupants were given the choice to help the robot if they were available, but did not have to help if they did not want to and could close their office doors to indicate that the robot should not ask them for help. Only one graduate student office emailed the authors to ask not to participate. As a result, CoBot sought help from each of 78 offices, nine times over three days (three times per day).

In order to compare occupants' availability to help with each request, CoBot attempted to ask each occupant for each type of help each day for a



within-subjects study design. In order to simulate an actual deployment of the robot, we:

- randomly assigned the order of the three requests each day such that each question was asked once per day and at different times on different days,
- randomly chose two of the nine requests to offer a gift of candy to represent the benefit provided when a robot performs services for them (i.e., brings mail).

The occupants each received at most two gifts total during Cobot's nine potential visits to reflect the fact that the robot will likely need help from an occupant even when they are not receiving some benefit (e.g., his/her mail). The assignment of gifts for each occupant was randomly chosen before the study started, and it was not guaranteed that the occupants would be available at the gift times. However, occupants were told about the gifts ahead of time so these gifts served as the incentives for occupants to help the robot.

The robot traversed the floor at 9:30 am, 12:00 pm, and 2:30 pm for three days along the same predefined path. The occupants were not able to see the wizard drive the robot or trigger the question from their offices. When the robot arrived at the door to each office, it first spoke "Hello" to get the occupant's attention and then spoke the the question and printed it on the laptop screen. The robot required participants to click on the laptop to respond. Upon pressing "Done," the robot would speak "Thank you" as an indication to the wizard to move the robot to the next office. Some occupants ignored the robot and did not click "No, I cannot help." After 10 seconds without a response from an occupant, the wizard timed out the question, moved the robot to the next office in the sequence, and this was logged as a refusal to help the robot. The wizard skipped offices that had closed doors.

After the study, the authors conducted interviews with occupants to understand their perceptions of the robot, their feelings about answering questions through the study, and to follow up on any observations about the occupants' interactions with the robot.

## 5.2 Robot Apparatus

In order to ensure that the robot stopped at the correct sequence of doorways, the wizard controlled the robot's motion and triggered the robot to speak the questions and display them on the screen. The screen interface on the robot's laptop contained one large text area with the question, and two buttons—"Yes, I am willing to help" and "No, I cannot help". For all questions, if the occupant clicked yes, the robot automatically provided instructions to click an additional "Done" button when the task was complete. Multiple choice locations were also displayed for the localization question. Whether the task was completed or not, the robot thanked the occupant and the wizard navigated the robot to the next office. As occupants clicked on the interface, it logged the office number along with the question type, responses to the question and the time stamp to use in the analysis. The occupants were required to use the screen interface—the robot did not respond to speech.

#### 5.3 Measures

In order to evaluate the willingness of occupants to answer the robot's questions we use four main measures: number of open doors, number of times occupants helped, locations of the occupants, and time spent responding. The number of open doors is an upper bound on the number of occupants who will help the robot. The number of times each occupant helped the robot allow us to understand the availability of humans to help the robot throughout the building. We determine whether there is a difference in response frequency and the amount of time it took occupants to respond to the different question types over time. Due to the small sample size (78 rooms tested nine times each), we only test for trends in our data and not statistical significance.

## 5.4 Results

Our results show that some, but not all, occupants were available to help the robot at any given trial and that they were largely distributed through the environment. Interestingly, this availability



changes by time of day but not depending on the type of question. Participants were equally willing to help with all types of questions although some took much longer than others.

Distributed Help In total, 130 doors were open out of a combined 702 in nine trials (Fig. 3a darker means the door was open more frequently). Occupants helped the robot 78 times out of the 130 possible open doors. 46 offices were open at least once and 31 of those offices contributed responses. Each office was open on average 1.8 (s.d. 1.9) times out of 9 possible and occupants answered on average 1.1 questions (s.d. 1.7). The high standard deviation for the offices indicates that there were a few occupants available almost all of the time, while many occupants were unavailable. Seven out of the 78 offices contributed 36 of the 78 responses to the robot. This indicates that there is a group of people that would likely be available for the robot to ask for help, although at any particular time there are likely to be many more occupants that the robot could ask to further distribute the help.

In terms of the question types, we found that each type of question took a very different amount of time to complete but occupants helped equally with them all. Occupants took on average 30.1 seconds (s.d. 18.1) to complete localization questions, 55.6 seconds (s.d. 24.6) for chair questions, and 88.3 seconds (s.d. 45.3) for the note writing questions. Despite these differences, when occupants were available to help, they were willing to answer any type of question. We found little difference in the response rate for each question type—57.5% of the localization questions, 62.5% of the chair questions, and 50% of the notes questions. This finding indicates that a robot would not need to reduce the asking frequency of questions that take longer to answer.

Fig. 3 a 130 doors were open out of 702 in nine trials (darker means the door was open more frequently). b Out of 130 open doors, 53 occupants in those offices refused to help the robot



(a) Total Open Doors

(b) Refused or Ignored Robot



Incentives We found no statistical difference in answering frequency when occupants were offered gifts to when they were not, but some occupants indicated in interviews that the gift did affect their decision to help. In particular, we observed some occupants deliberately opening their doors when they heard the robot down the hall so that they could help and possibly receive a gift. While gifts were only offered at random times, some participants stated in the interview that they would be more willing to help the robot if it offered candy more often.

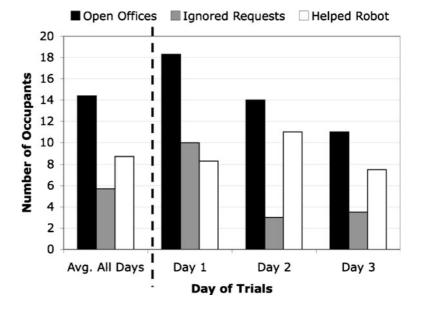
Long Term Interaction On an average trial, 14.4 (s.d. 7.5) doors were open, and occupants in those offices responded to the robot's requests for help 8.7 times and refused to help or ignored the robot the remaining 5.7 times (Fig. 4). However, there is a strong effect of day on the proportion of open offices and available helpers. The number of open office doors dropped each day likely due to occupants' prior knowledge about when the robot would be visiting. The number of occupants that did help the robot remained constant over the three days indicating less of a novelty effect for those seven occupants who helped the robot the most.

*Navigation* Figure 5a–c show the frequency of help from each office by time of day, with darker

colors representing more frequent help. Interestingly, the few frequently available occupants were largely distributed around the building - especially in the areas where the robot has the most uncertainty (Fig. 1b). A random selection of seven offices would not necessarily result in such an even distribution across the building. Every location in the building was at most ten offices from an occupant that helped the robot during many of the trials, except for the north side of the building at 2:30. Because the robot is least uncertain in the north side of the building, the robot may be able to navigate despite the low availability. However, the distance between available occupants indicates that the robot will have to plan its navigational paths to increase the likelihood of finding available occupants at execution time to complete its tasks.

To summarize, based on the initial questions we asked about office occupants, we found that some office occupants were willing to help the robot, although not all were. The number of people who helped the robot shows that it is feasible for a robot to use office occupants as **distributed help** through the building. Interestingly, this willingness to help was not affected by the length of time the question took to answer nor the **incentives** the occupants received. CoBot was able to collect data to begin to model the availability of

Fig. 4 On average, 14.4 (s.d 7.5) offices were open for each trial and 8.7 (s.d. 3.6) occupants helped the robot. While there were fewer open doors over time, more occupants with open doors were willing to help the robot







**Fig. 5 a–c** While occupants in each part of the building answered the robot's questions for most times of the day, we find almost no available occupants at 2:30 on the north

side of the building. The darker the office color, the more often the occupant responded to questions

different offices throughout the day and could continue to do this through long-term interactions. Because the occupants that helped CoBot were, for the most part, distributed throughout the environment, CoBot cannot assume that someone will be very close to help it and therefore must proactively navigate to those occupants in order to seek help.

By creating a model of occupants based on long-term interactions with them, we will show next that it is possible for the robot to plan paths that minimize its own limitations and increase the likelihood that occupants will be available to help when needed.

## 6 Proactive Navigation for Help

While previous work has taken into account the robot limitations, constraints, and uncertainty of

a path or state of a robot (e.g., [9, 13, 22]), little work has modeled the states and actions that can *resolve* such limitations such as human helpers [29]. Robots that depend on supervisors and bystanders often assume that their human helpers are always available (e.g., [3]). In these always-available cases, the robot need only determine when it requires help and does not take into account locations of available help to plan paths for its task.

However, when there is limited and/or probabilistic availability of human helpers distributed through the building, we argue that a robot should plan its paths to increase the likelihood of finding available occupants. The shortest distance path may result in a longer navigation time if there is high uncertainty along that path and no available occupants to help reduce that uncertainty. There are several planning frameworks that could possibly be modified to incorporate help from



occupants including traditional A\* path planners with added constraints [9, 13] and POMDPs that model human help [3].

We, first, contribute a model of the environment that includes spatially-situated occupants and their availabilities collected through long-term interactions. We, then, demonstrate one way to use this model for path planning, namely adapting the A\* algorithm to reason about the robot's capabilities and the available humans to help reduce limitations.

## 6.1 Model with Spatially-Situated Occupants

We define our model in terms of the building layout, robot capabilities and limitations, and occupant abilities. Our building layout includes:

- vertices V of locations in the building,
- edges E where  $e_{ij}$  is the hallway segment that connects  $v_i$  and  $v_j$ , and
- distances D where  $d_{ij}$  is the length of  $e_{ij}$

The robot navigates and performs services in the building with the following limitations:

- speed s which we assume, for simplicity, is constant over all edges,
- help types H that it requires to resolve its localization, perception, and actuation limitations,
- need matrix N where  $n_{ij}^h$  is the probability of needing help h on edge  $e_{ij}$ , and
- cost matrix C where  $c_{ij}^h$  is the time to autonomously overcome a limitation without asking for help h

For example, in our study, CoBot had three types of help: localization, perceiving and moving chairs, and writing notes to occupants. For localization,  $n_{ij}^{loc}$  is dependent on the robot's uncertainty on edge  $e_{ij}$  and CoBot does have the capability of overcoming its uncertainty without asking for help with a cost  $c_{ij}^{loc}$  that represents its replanning and relocalizing time. For the other two types of help, CoBot cannot perform the tasks autonomously so it always needs a human to help it  $(n_{ij}^h = 1)$  and the cost of performing autonomously is  $c_{ij}^h = \infty$ . For example, CoBot cannot move chairs or write notes, so the expected

time to complete these tasks on an edge is infinite. Our planner considers the expected time to traverse an edge  $t_{ij}$  to include the distances and velocity of the robot and its additional costs. With probability  $n_{ij}^h$ , the robot will experience cost  $c_{ij}^h$  on  $e_{ij}$ . Otherwise, it will not experience any cost.

$$t_{ij} = \frac{d_{ij}}{s} + \sum_{h \in H} \left( n_{ij}^h * c_{ij}^h \right) \tag{1}$$

In order for a robot in the environment to perform all of its tasks, we assume that the building layout includes offices with occupants on the edges. These occupants have the following constraints:

- availability A where  $a_{ij}^h$  is the probability of an occupant helping with type h on edge  $e_{ij}$  and
- response time R where r<sub>h</sub> is the average time it takes all occupants to respond to help h

Using this help, the robot can determine its new expected traversal time in terms of the availability of help and time for an occupant to provide that help. If the robot is uncertain and a human is available, the robot can traverse the next edge without  $c_{ij}^h$  but incurs a response cost  $r_h$ . If it is uncertain but no human is available, it traverses the edge with  $c_{ij}^h$ .

$$t_{ij} = \frac{d_{ij}}{s} + \sum_{h \in H} n_{ij}^{h} \left( a_{ij}^{h} r_{h} + \left( 1 - a_{ij}^{h} \right) c_{ij}^{h} \right)$$
 (2)

We can use the results from our study to define the availabilities on the edges and we found the average response times for the 3 types of help to 30.1, 55.6, and 88.3 seconds respectively. Next, we show one example of how a robot might use this model to determine its paths to navigate.

### 6.2 Navigating Towards Occupant Help

There are many possible planning algorithms that could take this new model into account. While models such as POMDPs can take into account uncertainty and availability for localization and navigation tasks, they cannot easily be adapted to actions or tasks in which the robot cannot function without occupant help, such as moving chairs



and writing notes. Instead, we chose to adapt A\* planners, because they

- are commonly used on robots today,
- can be applied to many different types of help we discussed previously and implemented quickly,
- and are easily modifiable by changing the edge weights to plan different shortest paths.

We will show that our planner consolidates all robot and occupant limitations and considers expected navigation time to both perform autonomously and ask for help.

Formally, a robot navigates along a path of edges in order to complete its tasks. We define a path  $p_b^g = \langle E_p \rangle$  from a beginning  $v_b$  to goal  $v_g$  as a set of edges that connect  $v_b$  to  $v_g$ , and  $P_b^g = \{p_b^g\}$  as the set of all such paths. Traditionally, the path with the shortest navigation time is the one with the globally shortest travel time:

$$\min_{p \in P_b^g} \text{DistOnly}(p) = \min_{p = \langle E_p \rangle \in P_b^g} \sum_{e_{ij} \in E_p} \frac{d_{ij}}{s}$$
(3)

A more realistic estimate of the shortest path takes into account uncertainty. Specifically, in addition to distance, we calculate the expected time to traverse the path in terms of the time to autonomously traverse the edges:

 $\min_{p \in P_b^g} \text{UncertDist}(p)$ 

$$= \min_{p = (E_p) \in P_b^s} \sum_{e_{ij} \in E_p} \left( \frac{d_{ij}}{s} + \sum_{h \in H} \left( n_{ij}^h * c_{ij}^h \right) \right) \tag{4}$$

This formulation assumes that the robot needs each type of help once per edge. If the edges are long, an extra parameter might be added to include multiple help costs.

When we include the human help available and the costs of needing help, the robot has the opportunity to resolve its uncertainty or limitations as it navigates autonomously or with help:

 $\min_{p \in P_b^g} \text{HelpUncert}(p)$ 

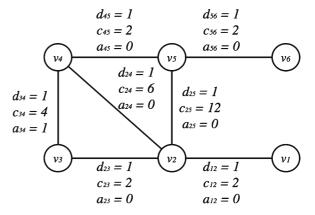
$$= \min_{p = \langle E_p \rangle \in P_b^g} \sum_{e_{ij} \in E_p} \left( \frac{d_{ij}}{s} + \sum_{h \in H} n_{ij}^h \left( a_{ij}^h r_h + (1 - a_{ij}^h) c_{ij}^h \right) \right)$$
(5)

Using this shortest navigation time formulation, we can show that a robot navigates towards available humans when the expected time to travel with a need for help is longer than the expected time to travel when stopping and asking for help. Because the robot can reason about its limitations and the availability of the humans in the environment, it can decide which path to take and when to ask for help and could easily be implemented in our environment. Additionally, as the expected availability of occupants in our environment (and many others) changes, the robot can replan its path to be sure someone is available to help it if necessary. Next, we provide an example of the differences between these plans and show that the shortest path can include human help to reduce the time to navigate autonomously.

## 6.3 Example

Figure 6 illustrates a simple example building with six vertices and relevant distances D, time costs C and availability A for a robot that only needs help with localization. For simplicity, we remove the help superscripts because there is only one type of help. We define the need for help for each edge  $n_{ij}$  to be 0.5. We evaluate which of the three noncyclic paths from  $v_1$  to  $v_6$  a robot should take:

-  $p_1$ :  $\langle e_{12}, e_{25}, e_{56} \rangle$ -  $p_2$ :  $\langle e_{12}, e_{24}, e_{45}, e_{56} \rangle$ -  $p_3$ :  $\langle e_{12}, e_{23}, e_{34}, e_{45}, e_{56} \rangle$ 



**Fig. 6** There are three paths from  $v_1$  to  $v_6$  and a human is available between  $v_3$  and  $v_4$ 

Using only the edge distances  $d_{ij}$ , the DistOnly travel time estimates are DistOnly( $p_1$ ) = 3, DistOnly( $p_2$ ) = 4, and DistOnly( $p_3$ ) = 5 respectively. When we account for the time to relocalize due to uncertainty using Eq. 4, path 2 is the shortest:

- UncertDist( $p_1$ ) = 11
- UncertDist $(p_2) = 10$
- UncertDist $(p_3) = 11$

In other words, if the robot were to navigate autonomously through this environment, it would be faster for it to take the second path rather than the first.

If we also include localization help based on the availability of humans in the offices on the edge between  $v_3$  and  $v_4$  using Eq. 5, the third path is the shortest. Because  $a_{ij} = 0$  for all occupants except between edge  $e_{34}$ , the  $a_{ij} * r$  term does not contribute to the traversal time of paths 1 and 2 and the expected times are the same as Eq. 4 (11 and 10 respectively). The expected cost of traversing the third path includes stopping and waiting for help on  $e_{34}$ :

- HelpUncert( $p_1$ ) = 11
- HelpUncert( $p_2$ ) = 10
- HelpUncert( $p_3$ ) = 9.25

The robot is able to plan to navigate toward the occupant for help rather than attempt to relocalize while traversing another path. Notice that if  $c_{25} = c_{24} = c_{34} = \infty$ , then the third path with help is the only valid one.

To summarize based on our original research questions, we have demonstrated that, using the locations and an availability model of the building occupants developed through **long-term interactions**, the robot can determine which offices to **navigate** to if it needs help. More importantly, we have demonstrated that the robot can find the shortest path to its destination which increases the likelihood that it will *pass by* many available offices so that it can proactively stop at those offices in case the robot needs help to overcome its limitations. The robot does not need to stop to request help if it can navigate autonomously. Our model can also be used by other planners such as POMDPs for localization and navigation.

Next, we discuss the opportunities to improve and extend the model using results from our post-study interviews.

#### 7 Discussion and Future Work

CoBot was able to elicit responses from many building occupants over the nine trials and collect information about who was available, where and when. Next, we discuss our qualitative observations and interviews with occupants after the study to illustrate opportunities to add further occupant constraints based on those results.

Interruption In designing the robot's initial interaction, we used an assumption that an open office door indicates that the occupant is interruptible. However, we found that often doors are left open even when occupants are in meetings or on the phone. Occupants who were in meetings and did not want to help the robot either verbally tried to send the robot away or ignored the robot until it left their doorway. Surprisingly, however, many occupants did interrupt their meetings or put their phone call on hold to help the robot and some reported that the interruptions were "well-needed breaks in their day."

Models of interruption have been used for supervisors to warn them about the robot needing help soon [35]. While it might seem obvious that a robot in human environments should also have a model of interruptibility through real-time sensing, a naïve interruption model may predict that occupants are not available to help when they are in meetings or on the phone [14]. However, if CoBot used this model, it would have received fewer responses compared to asking for help at every open door. A robot must learn, through its long-term interactions, which occupants are willing to be interrupted and under which conditions (e.g., who they are speaking with, whether they are working on the computer) to take full advantage of the occupant help.

Deception We also assumed that participants would answer the robot's questions accurately and completely when they agreed to help. While



occupants did answer 100% of the localization questions accurately, we found that several participants deceived the robot, responding that they moved the chairs or that they had written the note when they had not. In particular, two occupants submitted blank notes and two wrote notes with incomplete information about the package location.

It is unclear whether participants deceived the robot because they were told it was a study and not deployed for real. However, these results indicate that a robot must maintain some uncertainty about whether a task was actually performed for it. The robot could ask another occupant to confirm the task was completed since it may be difficult for the robot to detect deception itself, or otherwise use extra sensors to detect that the task was completed (e.g., a sensor near the paper and pens to detect if an occupant picked them up to write a note), or mitigate failures by apologizing and requesting help from someone else [23]. If the robot can determine and learn through its interactions over time which occupants are deceptive [10, 11], it should avoid asking for help from them in the future by either lowering the availability of the occupant or adding additional costs related to the trustworthiness of the occupants.

Question Repetition While most participants did respond to the repeated questions (each of the three questions were repeated each day), during the interviews, occupants reported that they were confused as to why the robot asked them to perform the same tasks multiple days in a row. One occupant reported that he wrote the incomplete notes out of frustration when he was asked to do the same task multiple times. This finding mirrors previous work that showed that people who are asked for help too frequently tend to stop responding to help requests in the future [32].

While this repetition of questions is an artifact of our study, it indicates the need for the robot to keep track of which occupants it has asked for help to purposefully plan to avoid those offices unless there is no other help available. This would require that the robot also model the history of questions to more heavily weigh the occupants who have not been asked for help recently. The robot would then need to model not only who is

available to help but the cost of asking someone too frequently, and the additional constraints for navigational planning and determining who to ask for help.

During actual deployments of a robot, however, reducing question repetition could be difficult. If only a single occupant is frequently available in areas of frequent limitations, the robot would have no choice but to travel in that area sometimes. In order to reduce the likelihood of this happening, it could request help from an occupant who is further away and is not asked for help as often. Additionally, the robot could include time in planning to vary the time of day it would complete the task (possibly delaying its task) if another occupant is available at another time.

Supervisors and Bystanders Finally, although our model is based on occupants and their availability and locations, this same model can be used to model supervisors and bystanders as well. Supervisors are typically equally available on all edges of the graph and can be modeled that way. However, if there is limited wireless communication range with the supervisor, for instance, the availability of the supervisor can reflect the signal strength of communication as the robot moves in the environment. The robot could then navigate towards the higher signal strength edges to ensure that the communication is clear to request help from its supervisor.

Robots that depend on bystanders assume that there is an even and high traffic flow along the path the robot could take. Instead, the availability of bystanders in our model could reflect the traffic flow through different areas of the graph. A robot that requests help from bystanders would then navigate towards a path with more people. In this way, it would be able to find help faster as it travels rather than necessarily waiting on low-traffic edges for help.

#### **8 Conclusion**

We have argued that robots that ask for help from occupants of the environment combine the



benefits of asking bystanders with those of supervisors in the following ways:

- Occupants have **incentive** to answer questions while the robot is completing services for others in order to reciprocate the help that other occupants provide the robot when it is performing services for them.
- The number of occupants can **distribute** the burden of help among many more people.

However, unlike supervisors and bystanders:

- Occupants are **not** always available to help the robot, and this availability can be measured through **long-term interactions**
- Occupants are spatially-situated and the robot must navigate to the occupants to receive help.

We have shown that, in terms of distributed help, several occupants were willing to help the robot with any of our three types of questions, irrespective of the question response time. Additionally, we found that some occupants were even willing to interrupt their meetings and phone calls to help the robot. In terms of incentives, we found no significant different in answering frequency when gifts were offered, but some occupants that expected gifts did open their door to help the robot. We found some novelty effect of occupants increasingly closing their doors over our three day study, but the number of available occupants remained constant. This indicates that a robot should be able to take advantage of occupant help over long-term interactions, and there are opportunities to learn availability based on the time of day from those interactions. We have introduced a model of the environment that includes the learned availability information, and demonstrated its use in an A\* planning algorithm. Finally, we discussed additional qualitative findings and opportunities to extend our model of humans in the environment to include other parameters such as interruptibility that can be learned through the long-term interactions with occupants.

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