HARPS: An Online POMDP Framework for Human-Assisted Robotic Planning and Sensing

Luke Burks, Hunter M. Ray, Jamison McGinley, Sousheel Vunnam, and Nisar Ahmed, Member, IEEE

Abstract—The ability of autonomous robots to model, communicate, and act on semantic “soft data” remains challenging. The human-assisted robotic planning and sensing (HARPS) framework is presented for active semantic sensing and planning in human–robot teams to address these gaps by formally combining the benefits of online sampling-based partially observable Markov decision process policies, multimodal human–robot interaction, and Bayesian data fusion. HARPS lets humans impose model structure and extend the range of soft data by sketching and labeling new semantic features in uncertain environments. Dynamic model updating lets robotic agents actively query humans for novel and relevant semantic data, thereby improving model and state beliefs for improved online planning. Simulations of a unmanned aerial vehicle-enabled target search in a large-scale partially structured environment show significant improvements in time and beliefs required for interception versus conventional planning with robot-only sensing. A human subject study in the same environment shows an average doubling in dynamic target capture rate compared to the lone robot case and highlights the robustness of HARPS over a range of user characteristics and interaction modalities.

Index Terms—Human–autonomy teaming, human–robotic interaction, multimodal interfaces, partially observable Markov decision processes (POMDPs), semantic data, target search and localization, uncrewed aerial systems (UAS).

I. INTRODUCTION

AUTONOMOUS robotic vehicles will greatly extend human capabilities in domains, such as space exploration [1], disaster response [2], environmental monitoring [3], infrastructure inspection [4], search and rescue [5], and defense [6]. Yet, the uncertain and dynamic nature of these settings, coupled with vehicle size, weight, power, and compute constraints (SWaP-C), often necessitates some form of human oversight to cope with the brittleness of autonomy [7]. This has created interest in new forms of human–robot interaction that can efficiently leverage human input to enhance robotic reasoning abilities. Probabilistic techniques relying on semantic-language-based human–robot communication have gained considerable attention for information fusion [8], [9], [10], [11], [12], [13] and task planning [14], [15], [16], [17], [18], [19]. However, existing approaches only allow robots to reason about limited kinds of uncertainties, i.e., as long as task environments and conditions are known a priori, or do not change in unforeseen ways. These approaches are antithetical to how human teams communicate with subtle ambiguities to express uncertainty. Constraining the types of information limits the flexibility and utility of semantic communication for adapting to new or unknown situations.

This work examines how robots operating in uncertain environments can use semantic communication with humans to solve the combined issues of model augmentation, multimodal information fusion, and replanning under uncertainty in an online manner. Such problems practically arise, for instance, with time-sensitive dynamic target search in areas with outdated or poorly defined maps, which lead to uncertain robot and target motion models as well as uncertain human input models.

A novel framework, human-assisted robotic planning and sensing (HARPS), is presented for integrated active semantic sensing and planning in human–robot teams, which formally combines aspects of online partially observable Markov decision process (POMDP) planning, sketch and language-based semantic human–robot interfaces, and model-based Bayesian data fusion.

As shown in Fig. 1, HARPS features three key technical innovations, which are developed and demonstrated in the context of dynamic target search tasks in uncertain environments. First, humans act as “ad hoc” sensors that push multimodal semantic data to robots via structured language, enabling robots to update task models and beliefs with information outside their nominal sensing range. This information can take the form of state observations, target dynamics, and problem structure, which can be represented by different modes in both robotic and human reasoning. Such distinctions allow multiple modes of information to be communicated and fused in an intuitive fashion while maximizing their utility to the robot. Second, humans can use real-time sketch interfaces to update semantic language dictionaries grounded in uncertain environments, thus dynamically extending the range and flexibility of their observations.

Manuscript received 20 October 2022; accepted 27 February 2023. Date of publication 19 April 2023; date of current version 8 August 2023. This work was supported by the Center for Unmanned Aircraft Systems (C-UAS), by the National Science Foundation Industry/University Cooperative Research Center (I/UCRC) under NSF under Grant CNS-1650468 along with significant contributions from C-UAS industry members. This paper was recommended for publication by Associate Editor Matthew Walter and Editor Wolfram Burgard upon evaluation of the reviewers comments. (Corresponding author: Nisar Ahmed.)

This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by University of Colorado Boulder Institutional Review Board under Application No. #20-0587, and performed in line with the Declaration of Helsinki.

The authors are with the Department of Smead Aerospace Engineering Sciences, University of Colorado Boulder, Boulder, CO 80309 USA (e-mail: luke.burks@colorado.edu; hunter-ray-1@colorado.edu; jamison.mcginley@colorado.edu; sousheel.vunnam@colorado.edu; nisar.ahmed@colorado.edu).

This article has supplementary material provided by the authors and color versions of one or more figures available at https://doi.org/10.1109/TRO.2023.3263460.

Digital Object Identifier 10.1109/TRO.2023.3263460.

Authorized licensed use limited to the terms of the applicable license agreement with IEEE. Restrictions apply.
Finally, robots actively query humans for specific semantic data on multiple modes to improve online performance while also planning with a foresight to act with imperfect human sensors. These features effectively enable online “reprogramming” of POMDPs together with human–robot sensor fusion to support online replanning in complex, dynamic environments.

This work introduces, describes, and demonstrates the following three novel technical contributions to the state of the art:

1) a novel framework for multimodal human–robot collaboration through structured semantic language interfaces;
2) dynamic, sketch-based modification of an online POMDP, evolving previous work [20] with novel computation allocation;
3) validated approach through human subject studies on a simulated dynamic target search problem.

These contributions significantly extend the earlier work in [20] in several important respects. First, although Burks and Ahmed [20] introduced the concept of the sketch-based modification of an online POMDP, it only considered limited types of dynamic semantic observation dictionaries that can be provided and fused by autonomous robots. The HARPS framework presented here not only accounts for collaborative semantic data fusion pertaining to dynamic state variables but also dynamic model and environment variables that impact robot motion and higher-level target state behavior in search problems. Second, while Burks and Ahmed [20] demonstrated a limited set of results in a simplified 2-D simulated environment, this article presents a more general and scalable implementation that is amenable to resource-constrained robots. This is also demonstrated here in a larger physics-based 3-D simulation, using more realistic robot motion, environmental, and sensing models. Finally, whereas our earlier work focused only on the algorithmic aspects of online modeling, data fusion, and planning, this article also applies HARPS in a thorough set of synthetic and live human subject studies to validate our approach and gain better insight into its utility for practical robotics problems.

The rest of this article is organized as follows. Section II presents motivating dynamic search problems and reviews methods for planning and semantic data fusion under uncertainty. Section III details the formal problem statement. Section IV describes technical details of the HARPS framework. Section V presents target search simulation results with simulated human sketch and structured language observations; Section VI presents the human subject study. Finally, Section VII concludes this article.

II. MOTIVATING PROBLEMS AND BACKGROUND

This work contributes an algorithmic framework that can be generalized to a variety of human–robot teaming scenarios. As robots gain greater autonomous capabilities, they need to recognize how to engage with their human collaborators to extract information about the environment and task at hand. Whether the operator acts in a supervisory or collaborative capacity, our framework enables their observations to augment autonomous robotic decision making. Facilitating robotic autonomy frees operators to focus on a variety of tasks, including allowing for a one-to-many framing of human–robot teaming [21], or coordinating operation within the context of a larger incident or team, such as in public safety [22].

During an evolving collaborative task between a human and a robot, natural uncertainties may arise due to incomplete prior information, including object location and associated dynamics models. Resolving these inconsistencies through semantic language provides an intuitive method of collaboration. However, robots need to be flexible with understanding new reference locations that may not have been known at the start and incorporate this variable and inconsistent human-generated “soft data” into their planning [10], [23].

This generalized problem is applied to a specific application of a dynamic target search task in which an uncrewed aerial system (UAS) must autonomously intercept a moving target as quickly as possible. The UAS must attempt to localize, track, and intercept a ground-based target within the span of its limited flight time. The environment, shown in Fig. 2, consists of a large, open space with a variety of distinct regions such as a farm, a neighborhood, mountains, hills, plains, and rivers. The robot only has a high-level map of the area available at the beginning of the search, such as a commercially available digital atlas, rendering specific locations and spatial extents of structures or landmarks within the environment unknown or incomplete a priori. The target can either drive through the local road network, which is fast but more spatially constrained, or proceed on foot in a slower yet unconstrained fashion. A remote operator is
available to help locate the target, and, with the help of various surveillance cameras, can communicate semantic information to the UAS regarding the target’s location, either upon request or in a volunteer capacity. They can also view the aircraft’s telemetry and video feed.

The UAS carries an optical sensor, which allows for high-probability target proximity detection that is subject to false alarms. It uses this information in conjunction with the operator’s semantic observations to update its belief of the target location before planning its own movements.

A. Language-Based and Sketch-Based Semantic Soft Data

The human primarily acts as an auxiliary and imperfect semantic information source that can interface with the robot at any time via either one of two methods. The first interface allows the human to compose linguistic statements that are parsed and interpreted as target state observations. As shown in Fig. 1, these are modeled in the structured form “Target is/is not Desc Ref,” where the Desc and Ref elements are taken from a defined set of semantic terms, i.e., a codebook, and the is/is not field toggles between positive and negative data [24]. In prior work [12], [13], [23], [25], [26], probabilistic likelihoods were developed for all possible statements in a given codebook to support recursive Bayesian fusion of linguistic human and robot sensor data. Since these works considered only fully-known environments, all relevant semantic references could be enumerated in advance. However, in the motivating problem, the space has not been mapped in high detail prior to the search, so the codebook is only partially defined at mission start. While this initially reduces the information available to the robot, the capability to reason and learn with sparsely detailed maps provides new opportunities for practical implementation.

This leads to the second interface. In cases where the recognition of key environmental features are not readily captured by robotic perception, due to factors such as onboard compute constraints or limited training data, codebook augmentations can instead be obtained from a human providing labeled 2-D freeform sketches, which each depict a spatially constrained region on a 2-D map display (as in Fig. 1 with “Pond” and “Trees”). Building on [20], the codebook is automatically augmented with the labels of new landmarks, so that the corresponding spatial sketch data can also be used to generate suitable soft data likelihood models for the linguistic statement interface (see Fig. 1). However, unlike in [20], human sketches here may also provide direct information about probabilistic state transition models to constrain how the robot and target may traverse certain map areas. While similar 2-D sketch interfaces have also been developed for robotics applications [14], [16], [27], [28], this work presents a novel use case in the context of multilevel data fusion for planning under uncertainty.

B. Optimal Planning and Sensing Under Uncertainty

The robot must autonomously generate its own plans for minimum time target interception, whether or not any semantic soft data are provided. The presence of model uncertainties, sensing errors, and process noise makes optimal planning quite challenging. One family of decision-making algorithms that accounts for these combined uncertainties is POMDPs. While POMDPs are impractical to solve exactly for all but the most simple problems [29], a variety of powerful approximations can exploit various features of particular problem formulations. A POMDP is formally specified as a 7-tuple \((S, A, \mathcal{T}, R, \Omega, O, \gamma)\), where the goal is to find a policy \(\pi\), which maps from a Bayesian posterior distribution, i.e., the belief \(b = p(s)\) over the set of states \(S\) with probability distribution \(p\), to a discrete action \(a \in A\). The transition model \(T\) is a discrete time probabilistic mapping from one state to the next given an action, \(p(s' | s, a)\), after which the robot is rewarded according to \(R(s, a)\). During policy execution, the robot receives observations \(o \in \Omega\) according to observation likelihood \(O = p(o | s)\).

For infinite horizon planning problems with discount factor \(\gamma \in [0, 1)\), and discrete time step \(k \in \mathbb{Z}^{0+}\), the optimal policy \(\pi^* (b(s)) \rightarrow a\) maximizes the expected future discounted reward:

\[
\mathbb{E} \left[ \sum_{k=0}^\infty \gamma^k R(s_k, a_k) \right].
\]

The primary challenge arising from casting our motivating problem as a POMDP lies in the ability of the human to modify the models \(T\) and \(O\) online in an unmodeled ad hoc fashion via the sketch interface. These modifications can happen rapidly and might change large swaths of each model with a single sketch. Bayes-adaptive POMDPs [30] allow POMDPs to learn the parameters of \(T\) and \(O\) but require gradual changes to their parameters and furthermore assume static \(T\) and \(O\). In the motivating problem, \(A, O,\) and \(T\) may change unpredictably with new sketches. This issue renders “full-width” offline point-based POMDP planners [31], [32] inapplicable, as they require models of how \(T, O,\) and \(\Omega\) change.

Online POMDP approaches [33], which eschew the process of pre-solving the policy prior to execution in favor of interleaving steps of policy execution and search, have successfully been used to address large observation spaces [34], continuous state spaces [35], and more recently, dynamic ad hoc models [20].
These algorithms make use of a “black-box” generative model, requiring only the “current POMDP problem” at time of execution, making them good candidates for solving problems with dynamic model uncertainty.

C. Active Semantic Sensing for Planning With Human Collaborators

A major challenge for problems such as target localization is that dynamics and uncertainties can easily become quite nonlinear and non-Gaussian, particularly given the types of semantic information available for fusion (e.g., negative information from “no detection” readings [36]). As a result, typical stovepiped approaches to control/planning and sensing/estimation can lead to poor performance, since they rely on overly simplistic uncertainty assumptions. Constraints on human and robot performance also place premiums on when and how often collaborative data fusion can occur. For example, it is generally important to balance situational awareness and mental workload for a human sensor (who might also need to switch between tasks constantly). Likewise, it is important for the robot to know how and when a human sensor can be exploited for solving complex planning problems, which would otherwise be very inefficient to tackle using only its own local sensor data. POMDP formulations offer a rigorous pathway to simultaneously addressing these issues, although approximations must still be considered for practical implementation [37].

One approach to POMDP approximation, the Q-Markov Decision Process (QMDP) algorithm [38], attempts to use a fully observable MDP policy to compute the optimal action in a partially observed step. As QMDPs are only exactly optimal assuming the state will, indeed, become fully observable after a single timestep, they are generally unsuitable for information-gathering-dependent problems such as the one addressed in this work. However, the introduction of the oracular POMDP (OPOMDP) formulation [39], [40] builds on a QMDP policy and enables the use of a human sensor to provide “perfect” state information at a fixed cost. Further work resulted in human observation provider POMDPs (HOP-POMDPs) [41], which allow the consideration of oracular humans who are not always available to answer a robotic query. HOP-POMDPs calculate a cost of asking, which is then weighed against the potential information value, similar to value of information (VOI)-aware planning in [9]. When augmented with the Learning the Model of Humans as Observation Providers (LM-HOP) algorithm [10], HOP-POMDPs can estimate both the accuracy and availability of humans, thus treating them as probabilistic sensors. A primary drawback to using either OPOMDPs or HOP-POMDPs to address target tracking problems is that while they both enable a QMDP-based policy to consider information-gathering actions, these actions consist of a single self-localization query. Such formulations ignore the rich information set available in the motivating problem thanks to the presence of semantically labeled objects. The present work addresses this limitation by expanding the information-gathering actions to include a broader set of queries regarding target position and dynamics.

D. Planning for Bidirectional Communication

Human–robot communication presents unique challenges in reasoning with respect to the complex nuances of natural language and human interaction. To perform comparably to an all-human team, robots working with humans benefit greatly from the ability to actively query their teammates to reason about given commands, aid collaboration, and update their understanding of the task or the environment. There is a substantial body of work on different aspects of natural language processing, for which Tellex et al. [42] provide a comprehensive review. Our motivating problem is similar to that of language grounding, where a system needs to reference a given command to a location within the environment. Methods proposed in [15] and [17] implement graphical models to reason over a teammate’s commands to aid in task planning. Spatial distribution clauses are used to infer a location-based hierarchy that allows a robot to reason over a wide range of commands. However, these approaches are limited by a static vocabulary that does not allow for the entry of new spatial or semantic information into the environment. As an environment may change over the course of an interaction or new environments are encountered, the vocabulary used to describe such environment must also be able to adapt, which is a focus of more recent work such as [43]. We obviate some of the challenging components of natural language processing by having the operator define physical locations using sketches in real time on a map, which the robot then uses as a spatial reference for integrating the provided observations and reasoning over queries to the operator.

While predefined interfaces, such as GPS coordinates, could be used to reason in a precise manner about geographic locations, this type of deterministic communication is unintuitive and prone to errors. Human teams will often communicate with inherent ambiguity necessitating follow-up questions between teammates to ensure comprehension. However, reasoning over this type of nuanced information remains challenging for robots. The method devised in [15] set up a framework for comprehending what information the user provided, whereas the authors in [44], [45], and [46] consider the problem of if, when, and what to communicate back to the user in order to resolve ambiguity across an interaction. These approaches utilize POMDPs to reason about some components of the human’s mental state in different collaborative tasks. The work presented in [47] shows how a POMDP can be utilized to refine the robot’s understanding of a human’s object of interest. In [48], a robot attempts to infer partially observable states of certain objects. However, in each of these cases, the user is limited in their vocabulary. These methods constrain the robot to communicate about a static and potentially obsolete environment, especially when applied in a dynamic target search where new locations become relevant to planning or querying.

In uncertain environments, new spatial information may be presented that, when reasoned over, can provide critical information to the completion of a task. The approach described in this work uses simplified compass-based spatial reference cues (North, South, Near, etc.) coupled with a dynamic vocabulary codebook that the user can update and modify in real time,
allowing the user to communicate to the robot teammate in an intuitive manner. Furthermore, the use of a POMDP to select the nature and timing of human communication enables reasoning with respect to the value of information theory proposed in [9].

III. FORMAL PROBLEM STATEMENT

The motivating problem is formally cast as a POMDP, specified by the 7-tuple \( \{ S, A, T, R, \Omega, \mathcal{O}, \gamma \} \). Let the continuous states of the mobile robot and target in some search environments be \( s_r \) and \( s_t \), respectively. The joint state space is \( [s_r, s_t]^T = s \in S = \mathbb{R}^N \), where \( N \) is the dimensionality of the combined state space. For the problem considered in this work, each agent is modeled in the 2-D plane, with the height of the mobile robot handled via an unmodeled secondary controller. This results in a combined state space with \( N = 4 \). The human sensor has full knowledge of \( s_r \) at all times as well the belief \( b(s_t) = p(s_t|o_{h}^{1:k}, o_{r}^{1:k}, a_{r}^{1:k-1}) \), which is the updated Bayesian posterior pdf given all observations made by the robot \( o_{r}^{1:k} \) and the human \( a_{h}^{1:k} \) through time \( k \). The action space \( A \) is a combination of movement actions made by the robot, which affects its state \( A_m \), and query actions, which pull information from the human \( A_q \).

The human has access to a limited set of camera perspectives that show a live feed of the simulated environment, shown in Fig. 2, which they use to gather information about the target’s location. They represent this information through sketches \( H \) and an associated spatial information cue (Near, Inside, North, South, etc.). The sketches are semantically labeled spatial areas corresponding to salient features of the space. These labels, along with problem-relevant relational indicators, form the semantic codebook from which the query actions \( A_q \) are drawn. The sketches themselves are defined geometrically, as a set of vertices forming a convex polytope in \( \mathbb{R}^2 \). Each sketch also corresponds to a softmax observation model like those used in [37] and [49], which is derived based on the polytope vertices [13] and is the observation model \( \Omega = p(o|s, a_q) \) for a given query action \( a_q \). An example softmax model is shown in Fig. 4.

The observation set \( \mathcal{O} \) is split into robotic detection observations \( \mathcal{O}_r = \{ \text{NoDetection, Detection, Capture} \} \) and human answers to query actions \( \mathcal{O}_h = \{ \text{Yes, No, Null} \} \), accounting for the possibility of the human not answering. Each sketch creates an enlarged query action space \( A_q' \) such that \( A_q \subset A_q' \), where each new action is a possible query to the human regarding the relative location of \( s_t \) with respect to the new sketch. For a given sketch labeled \( l \), with a set of relevant relational indicators, \( A_q' = A_q \cup [\text{Relation} \times l] \). Thus, the robot is capable of asking more questions after a sketch due to the expansion of possible semantic queries.

Finally, the reward function \( R \) is defined as a piecewise function to incentivize target capture and slightly penalize human queries such that for some distance threshold \( \tau \)

\[
R = \begin{cases} 
R_{c}, & \text{dist}(s_t, s_r) \leq \tau \\
R_{n}, & \text{dist}(s_t, s_r) > \tau, a_q = \text{Null} \Rightarrow \tau \\
R_{q}, & \text{dist}(s_t, s_r) > \tau, a_q \neq \text{Null} 
\end{cases}
\]

In this work, the capture reward \( R_{c} = 100 \), the cost of querying \( R_{q} = -1 \), and null query are allowed at no cost for \( R_{n} = 0 \). A POMDP policy \( \pi \) for this problem is one that maximizes sum of expected future discounted reward of actions \( E[\sum_{k=0}^{\infty} \gamma^k R^k] \), where \( R^k \) is the reward at time \( k \).

IV. TECHNICAL APPROACH

Many existing approaches for augmenting autonomous robotic reasoning with human–robot semantic dialog only allow robots to reason about limited kinds of uncertainties, such as assuming prior knowledge of task environments and conditions that do not change in unforeseen ways. This limits the flexibility and utility of semantic communication for adapting to new or unknown situations.

As shown in Fig. 1, this work features three key technical innovations. First, humans are modeled as ad hoc sensors that push multimodal semantic data to robots via structured language, enabling robots to update task models and beliefs with information outside their nominal sensing range. These multimodal inputs from the operator can update the POMDPs own observation models (\( \mathcal{O} \)) or action space (\( A \)), in addition to semantic information pertaining to previously abstracted or ignored state information, such as behaviors that change depending on the target mode. Such dynamic modeling was expressly forbidden by the techniques used in [37] and [49], which required a static, known POMDP 7-tuple, but are now accessible via ad hoc semantic sensor models.

Second, humans can use real-time sketch interfaces to update semantic language dictionaries grounded in uncertain environments, thus dynamically extending the range and flexibility of their observations. Finally, robots actively query humans for specific semantic data at multiple-task model modes to improve online performance while also planning with a foresight to act with imperfect human sensors. These features effectively enable online “reprogramming” of uncertain POMDPs together with human–robot sensor fusion to support online replanning in complex environments. These innovations are discussed in turn in each of the following sections.

A. Leveraging Operators as Sensors

1) Human Querying and Data Fusion: In this work, it is assumed that the human can act as either a passive semantic sensor, which volunteers information without request whenever possible, or as an active semantic sensor, which can be queried by the robot to provide information on request. This allows the human to proactively offer information they intuit to be useful, and for the robot to directly gather what it perceives to be the most vital information. However, as with many other sensor modalities, the use of a human sensor forces the consideration of sensor accuracy and responsiveness. An accurate characterization of these two attributes is necessary to determine the influence of the human’s information on the robot’s belief of the target location. In addition, the required value of such information needs to bear the cost of a query action when the sensor may not respond.
The human’s responsiveness to queries is based on a static a priori known availability value $\xi$, such that, for all human observations $o_h$ at all times, $p(o_h \neq \text{None}|s) = \xi$. This leads to an additional observation $o_h = \text{None} \in \Omega_h$. It is also assumed that the human has a static a priori known accuracy rate $\eta \in [0, 1]$. Within the space of all possible human observations $o_h \in \mathcal{O}$, a single observation $i$, such as “North,” can be mislabeled as a different observation $j$, such as “West.” We, therefore, account for the probability of an operator being wrong by redistributing the probability to the inaccurate observations:

$$p(o_h = j|s) = p(o_h = j|s) \cdot \eta$$

$$= \frac{1}{|\Omega| - 1} p(o_h = j|s) \cdot \eta \cdot p(o_h = (i \neq j)|s).$$

The notation $\bar{p}(o|s)$ and $\bar{p}(s'|s, a)$ denote models used during online execution, in contrast to the nominal distributions $p(o|s)$ and $p(s'|s, a)$. This parameterization of accuracy ignores the similarity between any two observations. For example, the probability mass associated with an observation “East” being inaccurate is not allocated primarily to “Northeast” and “Southeast,” but instead evenly allocated among all other possible observations. While this simplifies implementation and allows comparative testing of accuracy values, other models may yield more realistic results; e.g., linear softmax model parameters [20, 26, 50], can be used to determine the likelihood of mistaking semantic labels given $s$.

This work focuses on human operators represented as active sensors. This requires an explicit dependence on actions to be included in the observation model, as well as additional actions which trigger this dependence. Just as POMDP observations $o \in \mathcal{O}$ can be typically modeled as $o \sim p(o|s)$, human responses to robotic queries $a \in \mathcal{A}$ can be modeled as $o_h \sim p(o_h|s, o_h', a_h \in \mathcal{A}_h, o_h \in \Omega_h)$. These additional query actions can be introduced into $\mathcal{A}$ in one of two ways. Casting them as exclusive options, where either movement or a query can be pursued but not both, minimally expands the action space to the union of queries and movements, $\mathcal{A} = \mathcal{A}_m \cup \mathcal{A}_q$. But this can be limiting in situations, which benefit from rapid information gathering about models and states together. Instead, queries are cast as inclusive actions, in which every time step permits any combination of movement and query, $\mathcal{A} = \mathcal{A}_m \times \mathcal{A}_q$. This can drastically increase the size of the action space but allows rapid information gathering. A similar technique was successfully applied by Burks and Ahmed [20] for the more limited static semantic codebook case.

The robot’s onboard sensor produces a single categorical observation per time step $o_r$, which must be fused with $o_h$. We assume the robot’s sensor is independent of the human observations given the state such that:

$$p(s|o_r, o_h) = p(s)p(o_h, o_r|s) = \sum_{o_h} p(s)p(o_h|s)p(o_r|s).$$

Fig. 3 summarizes the probabilistic dependencies for the POMDPs describing the motivating search problem in Fig. 2.

While all observations are state dependent, some now depend on actions chosen by the policy. Also, query actions have no effect on the state and are pure information-gathering actions. In these new POMDPs, a combined action might be “Move to North, and Ask human if target South of Lake,” which may return a combined observation of “Target is Far from me, and human says target is not South of Lake.” So in this case $a = \{\text{North, South/Lake}\}$, and $o = \{\text{Far,No}\}$.

2) Multimodal Active Information Gathering: As described in the motivating problem of Fig. 2, the target can transition between two high-level modes, either constrained to the roadway or unconstrained on foot. These two modes carry their own transition dynamics and separately influence other state’s transitions. For example, the target cannot transition into the road-constrained state without first being near a roadway but can move much more quickly between spatial states once they have. To accommodate stochastic switching dynamics, it is generally convenient to include a finite number of discrete mode states $m$ as shown in Fig. 3, which dictate alterations to the target state transition models:

$$m = [s^T, m'], m' \sim p(m'|m), s' \sim p(s'|s, a, m').$$

This additional discrete state variable can be easily handled by POMCP and other Monte Carlo tree search approximations, which rely on generative black box simulators and support edits to $\mathcal{T}$ and $\mathcal{O}$. Offline approximations based on switching-mode POMDPs [51] can also accommodate hybrid dynamics but require stationary models. Such hybrid model extensions also open the door to active semantic queries and specific human observations $o_h$ pertaining to $m$ (e.g., “Is the target still traveling on the road”), which can greatly enhance the Bayesian belief for $m$.

With this modification to the generative model, the probability of different state transition models being in effect can be explicitly represented via particle approximation as:

$$P(m = x) = \frac{1}{N} \sum_{n=0}^N 1(m_n = x)$$

where $1(m_n = x)$ is an indicator function applied to the mode of particle ($n$).
For human responses modeled as $p(o_h|m)$, the belief update equation becomes

$$p(s|o_r, o_h) = \sum_{m} p(s, m|o_r, o_h)$$

$$= \sum_{m} p(s|o_r, o_h, m)p(m|o_r, o_h)$$

$$= \sum_{m} \frac{p(o_r|s)p(m|s)p(o_h|m)}{p(o_h)} p(o_r). \ (7)$$

If the mode $m$ is treated as a discrete addendum to the continuous state vector $s_t$, as in (5), this equation reduces to (4). The bootstrap particle filter used in Algorithm 2 approximates this belief update through the use of weighted particles.

### B. Using Structured Language and Sketches for Intuitive Interaction

1) Language-Based and Sketch-Based Semantic Soft Data: While addressing scenarios of unknown/dynamic environments, the human primarily acts as an auxiliary and imperfect semantic information source that can communicate with the robot at any time via either one of two interfaces, described in Fig. 1. The first interface allows the human to compose linguistic statements that are parsed and interpreted as target state observations, via the positive and negative semantic informational statements described in Section II-A.

The second interface addresses the novel problem of incorporating the human information into the robot’s map knowledge. Since new map information cannot be obtained from the robot’s sensor to augment the codebook, the human may instead do this by providing labeled 2-D free-form sketches, which each depict a spatially constrained region on a 2-D map display (as in Fig. 1 with “Pond” and “Trees”). While similar 2-D sketch interfaces have also been developed for robotics applications [14], [16], [27], [28], their use in the context of multimodal data fusion for planning under uncertainty represents a novel contribution.

Building on [20], the codebook is automatically augmented with the labels of new landmarks/references, and the corresponding spatial sketch data can also be used to generate suitable soft data likelihood models for the linguistic statement interface (see Fig. 1). However, unlike in [20], human sketches here may also provide direct information about probabilistic state transition models, to constrain how the robot and target may traverse certain map areas.

In this work, the model for the human sensor is assumed to be known in advance. That is, given a sketch $h_i$, the autonomy is capable of interpreting human responses to queries regarding $h_i$ according to a probabilistic likelihood function. Regarding the scope of human soft data in this work, such assumed models, including those for accuracy and availability, are further assumed to be static and are not learned or adapted online. Furthermore, while the online planning approach in the following sections could in principle be applied to changing reward functions without modification, here only changes to the observation function are considered. Such changes are taken “as

\[
\text{Algorithm 1: Sequential Convex Hull Reduction.}
\]

\textbf{Function: REDUCE}

\textbf{Input:} Convex Hull \(\{V\}\), Target Number \(N\)

\textbf{if} \(\{V\} == N\) \textbf{then}

\hspace{1em} return hull

\textbf{end if}

\textbf{for} \(v_i \in \{V\}\) \textbf{do}

\hspace{1em} \(\Theta(v_i) \leftarrow \text{angle}(v_{i-1}, v_i, v_{i+1})\)

\textbf{end for}

\textbf{\{V\} \leftarrow \{V\} \setminus \text{argmin}_v \Theta(v)\}

\textbf{return REDUCE(hull,N)}

is” by the autonomy, rather than maintaining a belief over the uncertain model parameters as in previous work [30].

Finally, the example problems in this work assume the semantic codebook to be empty at the start of the problem and built up from scratch by the human using semantically labeled sketches. However, the techniques for online planning and sketch processing apply identically in problems for which a prior codebook is available yet incomplete. In any case, building the codebook from scratch implies a slightly more difficult problem due to the potentially lacking information available at the start of the problem and, thus, provides a more compelling case for human sketch input.

2) Sketch Generation and Integration: A sketch, or drawing in the 2-D plane, begins as a set of points \(\{P\}\), whether with a pen, touchscreen, mouse, or other modality. The set \(\{P\}\) is tagged by the human with a natural language label \(l\), and any applicable metainformation \(\delta\). The communication of the label and metainformation in this work is accomplished using fillable text boxes and radio button selection of a preselected set of metadata options, but could also be acquired entirely from natural language through word association methods such as Word2Vec [52] or other deep learning methods.

From the set \(\{P\}\), the ordered vertices of a convex hull \(v_i \in \{V\}\), where \(\{V\} \subset \{P\}\) is obtained using the Quickhull algorithm. \(\{V\}\) is progressively reduced using Algorithm 1 until it reaches a predefined size by repeatedly removing the point contributing the least deflection angle to the line between its neighbors, calculated via the Law of Cosines for the vertex pair vectors $\vec{v}_{i-1} \vec{v}_i$

$$\Theta(v_i) = \arccos \left( \frac{\vec{v}_{i-1} \vec{v}_i \cdot \vec{v}_{i+1}}{||\vec{v}_{i-1} \vec{v}_i|| ||\vec{v}_{i+1} \vec{v}_i||} \right) \quad (8)$$
in a procedure inspired by the Ramer–Douglas–Peucker algorithm [53].

This heuristic was chosen as a proxy for maximizing the area maintained by the reduced hull, but, in practice, other heuristics could also be used. The reduced set is then used as the basis for softmax model synthesis [13], in which $M$ points define a final sketch $h_i$ associated with a softmax function with $|h_i| = M + 1$ classes. In general, these are the single interior class contained within the sketched polygon region and $M$ exterior classes distributed outside the sketched polygon region, each
Planning with Human Model Updates.

\textbf{Algorithm 2:} Planning with Human Model Updates.

1: \(B_k = \text{Particle Set (Size = N)}\)
2: \textbf{repeat}
3: \([a_m, a_q] = \text{POMCP}(B)\) (Ref. [33])
4: \(s \sim p_k(s|a_m)\) (unknown state)
5: \(o_r \sim \tilde{p}_k(o_r|s)\) (robot sensor observation)
6: \(o_h \sim \tilde{p}_k(o_h|s, a_q)\) (human query answer)
7: \(B_{k+1} = \text{Bootstrap Filter}(B_k, a_m, a_q, o_r, o_h)\)
8: \textbf{if} New Human Sketch (h) \textbf{then}
9: \(l = h.l, \) (human assigned label)
10: \(\Omega_{k+1} = \Omega_k \cup \{l \times \{\text{Near, E, W, N, S}\}\}\)
11: \textbf{end if}
12: \textbf{until} Scenario End

The query action set \(A_q\) and observation function \(\Omega\) are modified, introducing the newly minted sketch \(h_i\) \(\in \mathcal{H}\) and its corresponding softmax function such that the one shown in Fig. 4. The observation set \(\mathcal{O}\) remains the same in this work, but through the modified \(\Omega = p(o \in \mathcal{O}|s, a)\) observations corresponding to the new query actions in \(A_q\) are now available. The availability \(\xi\) and accuracy \(\eta\) parameters of the human collaborator are static across any model revisions, and their effect is folded into changes to \(\Omega\). In this way, both parameters are accounted for in planning through their effect on the observation likelihood.

In principle, the human could provide nothing more than the sketched points \(\{F\}\), with no label. However, the robot will still need to indicate specific sketches to the human in queries, potentially requiring it to resort to referring to “Sketch 1” versus “Sketch 2.” Semantic labeling of sketches ultimately leads to better understanding of the human’s part of the robot’s queries and, though not implemented here, enables the use of the semantic label to automatically infer additional metadata using natural language processing techniques. This metadata could be used to modify the robot’s transition function, such as pointing out a difficult sand trap.

C. Dynamic POMDP Modeling

Having updated the POMDP with revised observation likelihood through a human sketch, a POMDP planner can produce a new optimal policy. In this case, both the true and internal models of observations change with the sketch, as the human is able to specify their model directly through the sketch. The changed model implies that the robot must solve a different but related POMDP after each human sketch. With this in mind, we next consider viable approximations for solving such POMDPs.
by predicting which observation will be received. For a given action \( a_k \in A_k \) and belief \( b_k \), the observation model \( p(o|s) \) is used to direct tree samples to nodes with history \( b_k a_k o \). The weighted proportion of samples in nodes \( [b_k a_k o_1, b_k a_k o_2, \ldots, b_k a_k o_{|\Omega|}] \) represents the distribution \( p(o_k|b_k, a_k) \) (10)

\[
p(o_k = o|b_k, a_k) = \sum_{s_k \in b_k} w_{s_k} p(o_k = 1|s_k, a_k)
\]

which is the observation probability distribution for the belief and action. In order to spend \( \Delta t(a_k) \) time planning during the execution of \( a_k \), \( |\Omega| \) plans can be pursued, each allocated \( \Delta t(a_k) p(o_k = o|b_k, a_k) \) time. That is to say, after carrying out a belief update assuming a future observation, we generate a POMCP policy using time in proportion to the probability of receiving said observation. Upon receiving the true observation at the end of the action execution phase, the autonomous system can immediately begin executing the action from the policy corresponding to that observation. That is, having generated \( N_p \) policies \( \pi(o_{k+1} = 0), \pi(o_{k+1} = 1), \ldots, \pi(o_{k+1} = N) \), and received the observation \( o_{k+1} = 1 \), the policy \( \pi(o_{k+1} = 1) \) can be used to find action \( a_{k+1} \) without delay.

It must be noted that although this approach works well for all of the example application problems considered here (as there are only two observations the drone can receive during a movement action) it faces significant scalability issues. Creating and choosing between significantly larger numbers of predictive planning trees reduces the accuracy of the policy approximation sharply, especially if many observations hold similar likelihoods. This can be addressed in future work through a likelihood threshold to filter out rare observations, combined with a heuristic to determine actions when such rare observations are seen. Alternatively, observations could be collected into metawebuatations when they lead to similar beliefs, echoing the discretization of observations spaces seen in [55].

V. SIMULATED HARPS RESULTS

A. Observation Model Generation Pipeline

The HARPS simulation environment was developed in Unreal Engine 4 [56] to provide physics-based testing of POMDP tracking problems with human input. A drone, controlled through ROS [57] using the Microsoft Airsim API [58] attempts to localize, track, and intercept a ground-based target within an outdoor environment while interacting with a human supervisor through the sketch-based interface shown in Fig. 7. This PYQT5-based interface implements the information querying functionality with response buttons and drop-down lists, similar to the interface in [37], but populates the semantic codebook within from user sketches drawn directly on the map. The human can view the space either through a selection of security cameras, as shown in Fig. 2, or through a camera onboard the UAS.

To assess the ability of an online POMDP to work together with a broad range of human sensing characteristics to complete this task, a parameter study was first performed on a slightly simplified version of the HARPS environment built in Python 3.5. The parameter study examined a variety of parameterized human sensor characteristics for generating sketches and observations via the methods detailed in this work’s Supplementary

Fig. 5. Typical offline POMDP time allocation for planning and acting.

Fig. 6. Our framework allocates planning and acting over irregular time durations.
the target follows the switching Markov dynamics model in the road network problem, using an average speed of 20m/s and standard deviation of 5 m while on the road and 5m/s and standard deviation of 1 m while off-road. Query actions \( A_q \) were generated in real-time using the PSEUD algorithm, detailed in this work’s Supplementary Material.

HARPS uses a conical detection model for the aerial robot with a 30° viewcone \( v_c \) similar to that used in [37], with observation set

\[
O = \{ \text{None, Detected, Captured} \} \tag{12}
\]

and observation likelihood model with a 98% accuracy

\[
\Omega(\text{Captured}) = p(o = \text{Captured} | s) = 0.98 \tag{13}
\]

\[
\forall s | \text{dist}(s_t, s_r) \leq \tau \& s \in v_c
\]

\[
\Omega(\text{Detected}) = p(o = \text{Detected} | s) = 0.98 \tag{14}
\]

\[
\forall s | \tau \leq \text{dist}(s_t, s_r) \leq 2\tau \& s \in v_c
\]

\[
\Omega(\text{None}) = p(o = \text{None} | s) = 0.98 \tag{15}
\]

\[
\forall s | 2\tau \leq \text{dist}(s_t, s_r) \& s \in v_c.
\]

As HARPS is applied to a relatively larger-scale environment, with state space \( S \) comprising a 1000 m \( \times \) 1000 m area, the capture distance threshold \( \tau \) is set to 75 m. However, the restriction of detection and capture to the area under observation by viewcone \( v_c \) limits the ability of the robot to detect targets it is not directly facing as a result of movement actions \( A_m \).

The reward function was given a large positive reward \( R_c \) for the capture of the target within \( \tau = 75 \) m, and a small penalty of \( R_q \) for asking the human a question.

A variety of variables were tested to examine their influence on the robot’s ability to capture the target. These included the parameters accuracy, availability, and sketch rate, which dictate the human’s ability to provide information, as well as the use of the predictive tree search method, which modified the planner’s treatment of future observations. All statistical testing in the simplified HARPS environment was conducted using binomial significance tests on the ratio of successful captures by a given method when compared to a control.

C. Simulated Human-Assisted Versus Unassisted Performance

Table I compares the ability of the drone to intercept the target with and without human assistance. Each case was tested with \( N = 250 \) independent trials, with significance being determined via the binomial test. It is particularly important to note that the robot is able to locate and intercept the target in the majority of

![Fig. 7. HARPS user interface shows an overhead view of the operational area on the left, and live camera views from limited locations on the right. The structured language interface is available on the bottom right.](image-url)
cases using the POMDP planner even without simulated human intervention. With or without the human’s information, the online POMDP is still approximating an optimal policy for the information it has available. Far from minimizing the improvement shown in the “Human” case, the significant ($p < 0.05$) discrepancy with the “Nonhuman” case emphasizes that even an otherwise effective algorithm can still benefit greatly from the introduction of additional human information. The human case was run with a default accuracy and availability of 90%.

Qualitatively, the introduction of human information resulted in similar behavioral changes as in [37]. For example, in Fig. 9, without human input, either sketches or semantic observations, the robot engages in a broad-ranging patrol behavior, prioritizing well-connected nodes in the graph and eventually capturing the target as it ventured through a high-traffic area. However, the human case of Fig. 9 shows a more directed pursuit behavior, wherein the robot moves quickly toward the target area indicated by the human before firmly localizing and capturing the target. Note, this example does not imply all human cases were so direct, as examining the combined effects indicates a slight advantage as applied to the robot’s model of the human, allowing the difference between the true and assumed sensor dynamics to be examined. The full results of these tests, carried out for $N = 50$ independent trails for each combination of assumed and actual accuracy, are shown in Fig. 10. A human operating at 50% accuracy acts as a random observation generator and, therefore, does not produce significantly more captures than the earlier “Nonhuman” case. The 30% case allows the human observations to be taken in a negative form, still allowing useful information to be passed along.

The effects of both assumed and actual accuracy can also be seen in the rows and columns of Fig. 10. The average true accuracy shows similar results to the match case, with the averaging over assumptions compressing the range of results while the assumed accuracy displays no clearly significant effect. Naturally, there can be limits to such data in a marginalized form, as examining the combined effects indicates a slight advantage to a more pessimistic view of the human’s accuracy. That is, the upper-left triangle of results in which the human is more accurate than assumed performs slightly better on average than the lower-right.

**E. Human Accuracy**

After establishing the general effect of a simulated human collaborator on the effectiveness of the POMDP, specific attributes likely to vary between live subjects were examined. First, human accuracy was tested, using values in the set: $[0.3, 0.5, 0.7, 0.9, 0.95]$. That is, for a value of 0.7, the human would respond to questions correctly 70% of the time and incorrectly 30% of the time. These same values were tested as applied to the robot’s model of the human, allowing the difference between the true and assumed sensor dynamics to be examined. The full results of these tests, carried out for $N = 100$ independent trails, with significance being determined via the binomial test. In the blind case, planning is also carried out during the execution of the previous action, but using a belief predicated only on the expected dynamics update. This is opposed to the predictive method, which probabilistically allocates planning time among multiple possible observations to produce predicted measurement updates in addition to the dynamics update. Of note, the blindness of the baseline method only applies to a single step, as the full measurement update still occurs after the end of the current action, so it is at most one step behind. Here, the predictive tree search approach produces significantly ($p < 0.05$) more captures by aircraft operating within the 10 min search restriction. This may be attributable to the fact that the UAS moves at a slower speed than the target on the road and, therefore, timely arrival of a single positive measurement can have an out-sized effect on the ability of the drone to capture the target before it escapes the local area.

**TABLE II**

| Planning Type          | Capture Rate |
|------------------------|--------------|
| Blind                  | 0.76         |
| Predictive Tree Search | 0.85         |

In Table II, the predictive tree search method is tested against a baseline “blind” real-time planner. Each case was tested with $N = 100$ independent trails, with significance being determined via the binomial test. In the blind case, planning is also carried out during the execution of the previous action, but using a belief predicated only on the expected dynamics update. This is opposed to the predictive method, which probabilistically allocates planning time among multiple possible observations to produce predicted measurement updates in addition to the dynamics update. Of note, the blindness of the baseline method only applies to a single step, as the full measurement update still occurs after the end of the current action, so it is at most one step behind. Here, the predictive tree search approach produces significantly ($p < 0.05$) more captures by aircraft operating within the 10 min search restriction. This may be attributable to the fact that the UAS moves at a slower speed than the target on the road and, therefore, timely arrival of a single positive measurement can have an out-sized effect on the ability of the drone to capture the target before it escapes the local area.
Similar to accuracy, human availability was also tested across the same range of assumed and true values. Given the same size of $N = 50$, the results for the matched true to assumed availability did not indicate a strong effect. However, examining the marginal result distributions in Fig. 11, there is a clear positive trend line for true human availability while the effect of the robot’s assumption of the human’s accuracy is minimal.

**G. Sketch Rate**

Finally, the rate at which a human inserts additional sketch entries into the robot’s semantic codebook was examined. Simulated humans drew a sketch at a rate of [15, 30, 60, 120] s. For completeness, a trial was run in which the human was present but drew no sketches and introduced no new semantic information. As expected, this case of an infinitely long average sketching rate performed identically to the unassisted baseline. As shown in Fig. 12, there exists an optimal rate at which sketches provide a sufficiently diverse semantic codebook without overcomplicating the POMDP with additional actions to consider. This optimum, which peaked around one sketch per minute in this scenario, is likely highly problem dependent and represents a major consideration for any implementation of this work with live human collaborators. As additional sketches primarily modify the planning problem by increasing the number of actions to consider, this optimal rate represents the total volume of new environmental information that can be optimally reasoned over. It is possible that, having established for a particular problem the near-optimal sketch rate or volume, human collaborators could be coached or trained to adhere to it.

**H. Summary of Baseline Simulation Results**

These results taken together showcase the ability of the online POMDP planner to adapt to the human it is given, rather than requiring a collaborator with specific training or knowledge. Certainly, more accurate and available humans are of more use, but in no case tested across a range of simulated humans did the robot do significantly worse than the nonhuman baseline. This indicates that in the worst of cases, the POMDP is able to mitigate the effects of a poor human while maintaining its ability to effectively collaborate with others.

**VI. HUMAN SUBJECT STUDIES**

An institutional review board (IRB)-approved user study\(^1\) was run to test the effectiveness of the proposed approach using the same environment presented in Section III. The goal of the study was to evaluate the performance of the human–robot team with different communication abilities and compare the difference to an approach where the robot searches without human assistance. Communication modes include a passive operator that opportunistically provides observations to the robot, an active operator that can be directly queried by the robot, and a mixed, both approach where the operator provides information and responds to queries.

The study was devised as a within-subjects experiment, which tested a total of 36 subjects with varying levels of experience with autonomy and UAS. Subjects were tasked with assisting

\(^1\)University of Colorado Boulder IRB Protocol # 20-0587, approved Jan. 29, 2021.
the drone in capturing the target in each of three scenarios. They could observe the landscape for the target, or signs of the target, using seven different camera views distributed across the environment, as shown in Fig. 2. Sketches could be added on an accompanying 2-D map at any time, which also displayed the drone’s location and previous path.

In the active-only scenario, the subject could volunteer information only when requested by the robot. For example, the robot could ask “Is the target North of the Farm?”, to which the user could respond “Yes”, “No” or “I don’t know”. The passive-only scenario allows the subject to provide information without request whenever possible. This modality offered the subject the ability to provide positive or negative information about the target (is/is not), relative location (Near, Inside, North, South, East, West), and the associated sketch (“The target is inside the mountains”). Finally, the active/passive scenario combined the capabilities in the previous two other scenarios, allowing bidirectional communication between the robot and subject where the robot queried the user and the subject provided additional information as they saw fit.

Analysis of the results from the simulated user studies leads us to posit the six following hypotheses for the human subject studies. H1–H4 relate to objective measures, whereas H5 and H6 correspond to subjective measures.

H1: Respectively, incremental human input for the three scenarios, from active-only, passive-only, and active/passive will improve task performance.

H2: There exists a favorable frequency of human sketch input, such that too many sketches result in inefficient algorithmic planning and performance and too few sketches do not provide sufficient localization of the target.

H3: A more effective user, defined as having high levels of accuracy $\eta$ and availability $\xi$, will result in improved task performance.

H4: Subjects with better situational awareness, defined as those who switch to more camera views over time, will be more accurate.

H5: Subjects will have incrementally higher respective workloads for active-only, passive-only, and active/passive scenarios.

H6: Subjects will report higher levels of trust toward the robot with more interaction, with more accurate subjects reporting higher levels of trust.

H1 investigates the performance of the algorithm in the context of the unique modes available in an interaction. H2, H3, and H4 aim to evaluate the algorithm’s ability to handle a range of user types. H5 and H6 will provide insight into the user’s subjective view of the interaction with the robot across the respective modes.

A. Experimental Procedure

Upon recruitment to the study, subjects were given a briefing regarding the purpose and scope of the experiment. The experimentalist walked subjects through the interface and showed a brief video of the interaction. Once a subject read through the IRB-approved consent form, they were assigned a subject ID number and given the opportunity to experiment with the interface before starting the three trials. For each subject, the scenario ordering and target location were randomized between three initial targets and robot start points to account for learning improvements. For each scenario, subjects were given a maximum of 15 min (900 s) to find the target with the drone. The maximum time was increased from 10 min after preliminary human trails to allow for data collection. After each scenario, the subject filled out a questionnaire to rate their subjective workload and trust observations. Once all three scenarios had been finished, the subject was paid and dismissed.

1) Objective Measures: The objective measures used in this study can be broken down into metrics for performance, defined by time to capture (TTC), and user characteristics, which include their accuracy, availability, sketch rate, and view rate. Unless specifically broken out by scenario mode (active, passive, or both), the results for each subject are combined.

Performance:

1) Time to Capture: Defined as the time taken from the start of the simulation until the time where the robot came within 75 m to the target. If the drone failed to capture the target, then the TTC is not reported, and the scenario updates the capture rate for the respective run.

2) Capture Rate: The number of successful captures divided by the total number of runs for each category of scenario ($n = 36$).

User Characteristics:

1) Accuracy: For each observation provided by the subject, either passively or actively provided, an accuracy value, representing the truthfulness of the statement, can be reported using a softmax approximation as defined in Section IV. Equation (16) shows how the total accuracy is calculated where $p_o$ is the softmax-derived probability of the target being in the assigned label and $p_{\text{max}}$ is the maximum possible probability for that specific observation and target location. For comparison, a heuristic compass approximation is also calculated and whose total value is calculated according to (17). In this equation, $p_o$ similarly refers to the probability of the target being in the assigned label, although the definition constrains this value to $0.33 \leq x \leq 1$

$$\text{accuracy}_{\text{softmax}} = \frac{1}{N} \sum_{o \in O} \frac{p_o}{p_{\text{max}}}$$

$$\text{accuracy}_{\text{compass}} = \frac{1}{N} \sum_{o \in O} \left\{ \begin{array}{cl} 1 & p_o \neq 0 \\ 0 & p_o = 0 \end{array} \right.$$

2) Availability: The total questions answered divided by the total number of questions asked by the robot.

3) Sketch Rate: The number of sketches provided by the user divided by the scenario time. If the target was captured, then the TTC is used as the scenario time; otherwise, the duration of the scenario (15 min) is used.

4) View Rate: The rate at which a subject looks at different camera views is given by the total number of camera views divided by the scenario time.
TABLE III
PERFORMANCE METRICS FOR HUMAN SUBJECT STUDIES INCLUDING TTC, TTC STANDARD DEVIATION, AND CAPTURE RATE

| Mode         | Active | Passive | Both | No Human |
|--------------|--------|---------|------|----------|
| TTC (s)      | 302 ± 35 | 313 ± 40 | 305 ± 36 | 338 ± 61 |
| Capture Rate | 77.8%  | 88.9%   | 97.2% | 45.5%    |
| Workload     | 3.4 ± 0.2 | 3.3 ± 0.1 | 3.2 ± 0.2 | N/A      |
| Trust        | 3.6 ± 0.3 | 3.6 ± 0.2 | 4.0 ± 0.2 | N/A      |

2) Subjective Measures: At the conclusion of each trial, subjects were given questionnaires to assess their subjective workload, measured by the NASA RTLX survey, and their trust in the robot, using the Multi-Dimensional Measure of Trust (MDMT) survey.

The NASA Task Load Index (NASA-TLX) has been successfully applied across a range of domains to gauge user workloads [59]. We used a modified version known as the Raw TLX (RTLX) to simplify the questionnaires for the user. The RTLX is the most common modification to the classic TLX survey [60]. It dispenses with the relative weightings found in the classic TLX survey and simply takes the average of six questions that were reported on a scale from 0 (very low) to 7 (very high).

The MDMT survey was developed as a novel measurement tool to assess human–robot trust [61]. It gathers perceived trust across four differentiable dimensions, reliable, capable, ethical, and sincere, which are, respectively, gauged by a series of four questions. Each dimension can be further categorized into the broader factors of capacity trust and moral trust, of which we only focused on capacity trust. Each question is evaluated on an 8-point scale from 0 (Not at All) to 7 (Very) and can be ignored by the user if they deem it irrelevant. The total reported trust for each trial is calculated as the average of the answered questions.

B. Results

Participants were recruited from across the University of Colorado Boulder student body, as well as members of the local community. All 36 subjects were between the ages of 18–65 and reported 20/20 or correctable to 20/20 vision. While two subjects were professional UAS operators involved in surveying, and three subjects were active in search and rescue capacities, others came from a background with no UAS, aviation, or operational experience. There was also a range of experience with decision making algorithms as 15 (42%) of subjects reported no subject matter background and 9 (25%) reported high levels of familiarity. As a baseline metric of performance, the simulation was run without an active user for \( n = 40 \) trials.

1) Performance: H1 predicted that modes with more human input would improve overall task performance, the results of which are shown in Table III. The capture rate for each of the respective study modes shows a clear increase in capture rate with increasing levels of human interaction. When no human is present, the robot captured the target only 47.5% of the time, compared to the active human (77.8%), passive human (88.9%), and active/passive human (97.2%). Using a binomial significance test, all user cases are shown to be significant to \( p < 0.001 \) when compared to the robot-only situation. When the target was captured by the robot, the mean TTC is slightly higher for the robot-only case and does not have a significant variation across all of the interaction modes. However, it is important to consider that the mean TTC does not account for instances where the robot failed to capture the target. While the mean TTC is not statistically significant on its own, the doubling in capture rate from the robot-only mode to the active/passive human mode, and incremental improvement across interaction modes, substantiates H1.

2) User Type: The tested subjects compromised a wide range of interaction styles and consistencies. Fig. 13 shows each subject’s performance across all three scenarios sorted by mean TTC. Some users, such as subjects 2, 3, 4, and 5 showed consistently low mean TTC. Alternatively, other users such as subjects 32, 33, and 35 showed repeated failures to capture the target and a wide standard error across their respective scenarios. There were other instances, such as with subject 1, where the target was captured primarily through luck for one mode of interaction and failed to capture to target on the other two modes. These trends are indicative that the method by which the user interacts with the agent can have a substantial effect on their resulting performance. Analysis of sketch frequency, user accuracy, availability, and number of camera views attempt to quantify the particular variables that influence the success of each interaction.

H2 predicted that there would be an optimal frequency of sketches, such as that found in the simulated experiments. Users drew anywhere from 1 to a maximum of 14 sketches throughout the simulation, some examples of which are shown in Fig. 14. While some users preferred to draw a series of sketches prior to searching for the target, others would only draw sketches when the target had been observed. Unlike the simulated HARPS environment, there was no clear correlating trend for user performance and the number of sketches that had been drawn. In fact, the scenarios with three of the top four highest number of sketches drawn (14, 13, and 11 sketches) failed to capture the target, with the robot demonstrating poor planning behavior, such as repeated routes. The inefficient planning stems from an exponential growth in action space with each added sketch. As subjects were able to capture the target in less than 2 min with
as few as one sketch and as many as nine sketches, there does not prove to be a favorable number or frequency of sketches that results in optimal performance; therefore, we do not have enough evidence in favor of hypothesis H2.

H3 predicted that more effective users would lead to improved performance. Semantic accuracies $\eta$ for softmax and compass values were calculated according to (16) and (17). When accuracies are evaluated for all scenarios, there are no clear correlations as capture times of 200 s maintained a wide range of values from 0 (completely inaccurate) to 1 (completely accurate). This variance may be due to users providing helpful information that was not completely accurate but drew the drone toward where they may have seen to target. A more effective analysis compares each users’ overall accuracy to their mean TTC for all three scenarios. These results are shown in Fig. 15, which shows a statistically significant ($p < 0.05$, $R^2 = 0.11$, $t(23) = -2.3$) decreasing trend of lower user accuracy leading to poor performance.

However, user availability did not show any clear trends when compared to user performance. The average user availability was 57%±19%, which reflects the fact that users would answer about every other question posed by the robot. The frequency of questions asked by the robot varied throughout the simulation. The unpredictable nature caused some to users comment that it was challenging to notice that a question was being asked and respond to it in a prompt and accurate manner. Wide variability existed even for successful users as one subject captured the target in 188 s with an availability of 31% while another user finished at 168 s with an availability of 80%. This observed contrast in conjunction with the accuracy trends demonstrates that the quality of information provided is more valuable than the quantity of observations. Hypothesis H3 is, therefore, partially proven with the caveat that effective users are defined by higher accuracy while availability is not a significant factor.

H4 predicted that situational awareness could be measured by camera view and lead to higher performance. However, the trends are inconclusive. Users who observed more cameras per second performed slightly better than others; however, not enough data are available to prove that these are indicative of a larger trend. There was also no relationship between the view rate and user accuracy. These results indicate that hypothesis H4 cannot be substantiated.

3) Subjective Metrics: H5 predicted that more interaction with the robot would lead to higher operator workload. Table III shows the total workload across the three different user modes. The average total reported workload across all three conditions demonstrates minor increases for active ($\mu = 3.2 \pm 0.15$), passive ($\mu = 3.3 \pm 0.14$), and active/passive ($\mu = 3.4 \pm 0.16$) modalities. Overall, the workload did not seem to be significant with one user reporting that, “There was not a lot of workload.” Methods of reporting workload in a consistent manner across different subjects is an ongoing area of study [60]. These challenges merit the consideration of each subject’s relative ranking of the
workload for each mode. Evaluating the relative workload from this perspective, the combined active/passive condition resulted in the highest level workload for 20/36 subjects, versus the active and passive cases, respectively, providing the highest workload for 16/36 subjects. Therefore, while hypothesis H5 cannot be substantiated, it is worthy of note that the active/passive condition had the highest relative level of workload, whereas the passive and active scenarios displayed relatively equal rankings across subjects.

H6 predicted that more interaction with the robot would lead to higher levels of trust. Evaluating the total reported trust across the different scenarios and subjects using a z-test, there is a moderately significant ($p < 0.07$) difference between the reported trust for the active/passive case ($\mu = 4.03 \pm 0.22$) versus the passive case ($\mu = 3.47 \pm 0.24$), which had the lowest overall trust. In postsimulation questionnaires, one subject noted that “Having the drone ask questions and respond according to my answers built trust”. This may be indicative that giving the agent the capability to ask questions provides the user insight into its understanding of the mission. In evaluating hypothesis H6, there are no clear trends between user trust and user accuracy. However, in Fig. 16, a statistically significant ($p < 0.01$, $R^2 = 0.15$, $t(93) = -4.2$) trend developed between user trust and scenario mean TTC, with lower TTC strongly correlating to higher trust.

C. Discussion

The human subject studies demonstrate that the proposed algorithm maintains strong performance while reasoning over a wide range observation accuracies and user behaviors from the provided semantic sketch information and query responses. The interaction did not significantly burden the users and the ability of the robot to offer bidirectional communication improved users’ trust in the agent. Additional training may also improve the frustration felt by several users by clarifying robot intent and behavior.

The human subject studies also showed differences from the simulated study results. Most notably, the simulated results captured the targets more often than the humans did in the active case. This is likely due to the randomized starting conditions used in the simulated experiments versus the three static start points in human experiments. Furthermore, aspects of human cognition, in addition to accuracy and availability, that were unmodeled by the POMDP may have played a role. Future work will be required to identify additional cognitive features to improve cooperation with human.

Calculating the user’s accuracy as a single number disposes of the nuance in each observation. For example, the interaction in Fig. 17 shows the user providing an objectively incorrect first observation that the target was inside sketch “area1”. However, this information compelled the robot to move in that general direction and follow-up questions to the user narrowed the robot’s belief of the target resulting in a capture. In this interaction, the user likely confused the proper location of the target on the 2-D map, favoring a prompt coarse observation in the target’s general vicinity.

In a different scenario (not shown), the user knowingly provided false information in order to steer the drone away from the town at the NW corner of the map. Due to the density of roads in this area, the drone often gravitated in this direction and user observations were helpful in getting it to explore other areas. In this case, a negative observation that the target was not in the town would have been equally helpful. Once out of the area, a subsequently accurate observation by the user helped the robot catch the target.

Despite these nuances, the significant trend correlating user’s overall softmax accuracy to performance, in comparison to the cruder compass metric, validates the implementation of the softmax approximation in Section IV.

Notably, the algorithm encouraged users to interact with the interface in a personalized manner. Fig. 14 shows how users chose to draw sketches around notable landmarks, at camera locations, or solely around the perceived target. Each of these methods resulted in the target being captured, particularly if the observations provided were followed up from numerous reference points. Users that failed to perform adequately often did not treat the robot as a teammate, instead trying to direct the
drone to regions that they wanted it to visit, such as in Fig. 18, or giving a standalone observation from a single reference point. While standalone observations were considered sufficient by some users, the robot’s ability to ask follow-up questions showed an improvement in performance and a significant increase in user trust. However, numerous subjects reported frustration in dealing with the robot as it seemed to not take their observations into account. Due to the nonintuitive nature of the actions determined by the online POMDP planner, the drone displayed complex behavior such as not going directly to the area mentioned to cut-off possible escape locations. Sometimes, this frustration turned to surprise as the target was subsequently caught, such as when one user noted, “I still couldn’t figure out what the robot was doing sometimes and why it was flying in certain directions. This made me think it wasn’t as consistent and predictable. It was quite competent in the end at accomplishing the task.” Subjects mentioned that continued interactions with the robot improved their understanding of effective interaction methods commenting that “I think the practice from the previous rounds made it easier to determine what to do this round.” In our study, the subject briefing was left intentionally vague to evaluate the intuitive nature of the interaction. However, like any collaborative task with a teammate, joint training would likely improve performance as robot behavior becomes less opaque.

To improve the collaborative nature of the searching task, future work may incorporate nonbinary observations of the target. For example, instead of only being offered an option of “Is/Is not” in the structured language observation menu, a user could express their own uncertainty with nuanced observations such as probably/probably not. While these observations would be more challenging for the robot to reason through, the user may be compelled to provide extra information when they have only a vague understanding of the target location. Adding degrees of uncertainty to observations naturally extends the uncertainty enabled through the sketch-based interface and replicates how humans communicate with each other in dynamic environments.

**VII. CONCLUSION**

This article presented and demonstrated the HARPS framework, a novel approach to multilevel active semantic sensing and planning in human–robot teams in unknown dynamic environments. We extend online POMDP planning frameworks to incorporate semantic soft data from a human sensor about uncertain dynamic task states, shared from human to robot through the use of a sketch-based semantic structured language interface. Enabling this interaction is a novel formulation of a POMDP with a “human-in-the-loop” active sensing model, as well as innovations to the use of soft-data fusion that allow the communication of higher-level modal information. The approach was demonstrated and evaluated on a relevant dynamic target search problem with real and simulated operators, which highlighted the improvements that query to a human can bring to a collaborative target search problem. The results show the simulated robot effectively using localized sketches and binary observations in response to language-based queries to intercept a moving target. The human subject studies validated the effectiveness of the algorithm in extracting information from users in a wide range of interaction styles and showed that active querying increased user trust in the robot without adding excessive workload.

The realized system enables robust, intuitive human–robot collaboration in unknown, dynamic environments. The introduction of a dialog based on sketches and colloquial language creates new opportunities for operators to engage with robotic systems in diverse manners, enabling the communication of accurate and useful information without the need to insist on machine-level precision from humans. Furthermore, extensive live and simulated testing inspires high confidence in the system to adapt to any human, rather than relying on operators with specific training, skill sets, or knowledge bases. This combination of decreased reliance on high-precision humans and increased tolerance of human-introduced uncertainty dramatically expands the space of useful applications for human–robot teaming with respect to the previous state of the art.
REFERENCES

[1] S. McGuire, P. M. Furlong, C. Heckman, S. Julier, D. Szafir, and N. Ahmed, “Failure is not an option: Policy learning for adaptive recovery in space operations,” IEEE Robot. Automat. Lett., vol. 3, no. 3, pp. 1639–1646, Jul. 2018.

[2] J. Delmerico et al., “The current state and future outlook of rescue robotics,” J. Field Robot., vol. 36, no. 7, pp. 1171–1191, 2019.

[3] M. Dunbabin and L. Marques, “Robots for environmental monitoring: Significant advances and applications,” IEEE Robot. Automat. Mag., vol. 19, no. 1, pp. 24–39, Mar. 2012.

[4] M. Hutter et al., “Towards a generic solution for inspection of industrial sites,” in Field and Service Robotics. Berlin, Germany: Springer, 2018, pp. 575–589.

[5] M. Goodrich, B. Morse, C. Engh, J. Cooper, and J. Adams, “Towards using unmanned aerial vehicles (UAVs) in wilderness search and rescue: Lessons from field trials,” Interact. Stud., vol. 10, pp. 453–478, 2009.

[6] R. A. David and P. Nielsen, “Defense science board summer study on autonomy,” Defense Sci. Board, Washington, USA, Tech. Rep. AD1017790, Jun. 2016.

[7] J. M. Bradshaw, R. R. Hoffman, D. D. Woods, and M. Johnson, “The seven deadly sins of ‘autonomous systems’,” IEEE Intell. Syst., vol. 28, no. 3, pp. 54–61, May/Jun. 2013.

[8] F. Bourgault et al., “Scalable Bayesian-human-robot cooperation in mobile sensor networks,” in Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst., 2008, pp. 2342–2349.

[9] T. Kaupp, A. Fukarenko, and H. Durrant-Whyte, “Human–robot communication for collaborative decision making: A probabilistic approach,” Robot. Auton. Syst., vol. 58, no. 5, pp. 444–456, 2010.

[10] S. Rosenthal, M. Veloso, and A. Dey, “Learning accuracy and availability of humans who help mobile robots,” in Proc. 25th AAAI Conf. Artif. Intell., 2011, pp. 1501–1506. [Online]. Available: https://www.aaai.org/ocs/index.php/AAAI/AAAI11/paper/view/3665/4114

[11] A. N. Bishop and B. Ristic, “Fusion of spatially referring natural language statements with random set theoretic likelihoods,” IEEE Trans. Aerosp. Electron. Syst., vol. 49, no. 2, pp. 932–944, Apr. 2013.

[12] N. R. Ahmed, E. M. Sample, and M. Campbell, “Bayesian multicalssification soft data fusion for human–robot collaboration,” IEEE Trans. Robot., vol. 29, no. 1, pp. 189–206, Feb. 2013.

[13] N. Sweet and N. Ahmed, “Structured synthesis and compression of semantic human sensor models for Bayesian estimation,” in Proc. Amer. Control Conf., 2016, pp. 5479–5485.

[14] M. Skubic, C. Bailey, and G. Chronis, “A sketch interface for mobile robots,” in Proc. IEEE Int. Conf. Intell. Syst., Man, Cybern., Conf. Theme: Syst. Secur. Assurance, 2003, vol. 1, pp. 919–924.

[15] S. Tellex and B. Ristic, “Fusion of spatially referring natural language commands for robotic navigation and mobile manipulation,” in Proc. 25th AAAI Conf. Artif. Intell., 2011, pp. 1507–1514.

[16] Z. N. Sunberg and M. J. Kochenderfer, “Online algorithms for POMDPs with continuous state, action, and observation spaces,” in Proc. 28th Int. Conf. Automat. Plan. Scheduling, 2018, pp. 259–263.

[17] E. Sample, N. Ahmed, and M. Campbell, “An experimental evaluation of humans who help mobile robots,” in Proc. IEEE/RSJ Int. Conf. Hum.oid Robots, 2014, pp. 741–747.

[18] W. Koch, “On ‘negative’ information in tracking and sensor data fusion: Discussion of selected examples,” in Proc. 7th Int. Conf. Intell. Fusion, 2004, vol. 1, pp. 91–98.

[19] L. Burks et al., “Collaborative human-autonomy semantic sensing through structured POMDP planning,” Robot. Auton. Syst., vol. 140, 2021, Art. no. 103753.

[20] M. L. Litman, A. R. Cassandra, and L. P. Kaelbling, “Learning policies for partially observable environments: Scaling up,” in Proc. 12th Int. Conf. Mach. Learn., 1995, pp. 362–370.

[21] N. Armstrong-Crews and M. Veloso, “Oracular partially observable Markov decision processes: A very special case,” in Proc. IEEE Int. Conf. Robot. Automat., 2007, pp. 2477–2482.

[22] N. Armstrong-Crews and M. Veloso, “An approximate algorithm for solving oracular POMDPs,” in Proc. IEEE Int. Conf. Robot. Automat., 2008, pp. 3346–3352.

[23] S. Rosenthal and M. Veloso, “Modeling humans as observation providers using POMDPs,” in Proc. RO-MAN, 2011, pp. 53–58.

[24] S. Tellex, N. Gopalan, H. Kress-Gazit, and C. Matuszek, “Robots that use language,” in Proc. Ann. Rev. Control Robot., Auton. Syst., 2020, pp. 25–55.

[25] M. Berg, D. Bayazit, R. Mathew, A. Rotter-Aboyoun, E. Pavlick, and S. Tellex, “Grounding language to landmarks in arbitrary outdoor environments,” in Proc. IEEE Int. Conf. Robot. Automat., 2020, pp. 208–215.

[26] V. Unhelkar, S. Li, and J. Shah, “‘Semi-supervised learning of decision-making models for human-robot collaboration,’” in Proc. Robot. Learn., Mach. Learn. Res., 2020, vol. 100, pp. 192–203. [Online]. Available: http://proceedings.mlr.press/v100/unhelkar20a.html

[27] V. Unhelkar, S. Li, and J. Shah, “Decision-making for bidirectional communication in sequential human-robot collaborative tasks,” in Proc. IEEE/ACM Int. Conf. Human-Robot Interact., 2020, pp. 329–341, doi: 10.1109/31902.3374779.

[28] S. Nikolaidis, M. Kwon, J. Forlizzi, and S. Srinivasa, “Planning with verbal communication for human-robot collaboration,” J. Human-Robot Interact., vol. 7, no. 3, Nov. 2018, Art. no. 22. [Online]. Available: https://doi.org/colorado.idm.oclc.org/10.1145/3203545.

[29] E. Rosen, N. Kumar, N. Gopalan, D. Ullman, G. Konidaris, and S. Tellex, “Mixed reality as a bidirectional communication interface for human–robot interaction,” in Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst., 2020, pp. 1–9.

[30] N. R. Ahmed, M. Campbell, and T. M. Howard, “Real-time human-robot communication for manipulation tasks in partially observed environments,” in Proc. Int. Symp. Expr. Robot., 2018, vol. 11, pp. 448–460. [Online]. Available: https://doi.org/colorado.idm.oclc.org/10.1109/7978-3-030-33950-0_39
Luke Burks received the B.S. degree in physics from the University of Arkansas, Fayetteville, AR, USA, in 2015, and the Ph.D. degree in aerospace engineering sciences from the University of Colorado Boulder, Boulder, CO, USA, in 2020, focusing on optimal planning and sensing in human–robot teams.

He is currently a Research Engineer and a co-lead of the Humans and Autonomy Research Group, Aurora Flight Sciences, Manassas, VA, USA. His research interests include algorithms for optimal decision making under uncertainty and probabilistic inference for human–autonomy interaction.

Hunter M. Ray received the B.Sc. degree in mechanical engineering from Brown University, Providence, RI, USA, in 2018, and the M.S. degree in aerospace engineering in 2021 from the University of Colorado Boulder, Boulder, CO, USA, where he is currently working toward the Ph.D. degree in aerospace engineering from Ann and H.J. Smead Aerospace Engineering Sciences Department.

His research interests include the development of intuitive robotic interfaces and probabilistic algorithms that enable human–autonomy teams.

Jamison McGinley received the B.S. and M.S. degrees in aerospace engineering from the University of Colorado Boulder, Boulder, CO, USA, in 2019 and 2022, respectively.

Sousheel Vunnam received the B.S. degree in computer science from the University of Colorado Boulder, Boulder, CO, USA, in 2019.

Nisar Ahmed (Member, IEEE) received the B.S. degree in engineering from Cooper Union, New York, NY, USA, in 2006, and the M.S. and Ph.D. degrees in mechanical engineering from Cornell University, Ithaca, NY, in 2012.

He is currently an Associate Professor and an H.J. Smead Faculty Fellow with Smead Aerospace Engineering Sciences Department, University of Colorado Boulder. He directs the Cooperative Human-Robot Intelligence (COHRINT) Lab, University of Colorado Boulder, which researches probabilistic modeling, estimation, and control of autonomous systems, human–robot/machine interaction, sensor fusion, and decision-making under uncertainty.