Multi-Agent Active Search using Realistic Depth-Aware Noise Model

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Abstract—The search for objects of interest in an unknown environment by making data-collection decisions (i.e., active search or active sensing) has robotics applications in many fields, including the search and rescue of human survivors following disasters, detecting gas leaks or locating and preventing animal poachers. Existing algorithms often prioritize the location accuracy of objects of interest while other practical issues such as the reliability of object detection as a function of distance and lines of sight remain largely ignored. An additional challenge is that in many active search scenarios, communication infrastructure may be damaged, unreliable, or unestablished, making centralized control of multiple search agents impractical. We present an algorithm called Noise-Aware Thompson Sampling (NATS) that addresses these issues for multiple ground-based robot agents performing active search considering two sources of sensory information from monocular optical imagery and sonar tracking. NATS utilizes communications between robot agents in a decentralized manner that is robust to intermittent loss of communication links. Additionally, it takes into account object detection uncertainty from depth as well as environmental occlusions. Using simulation results, we show that NATS significantly outperforms existing methods such as information-greedy policies or exhaustive search. We demonstrate the real-world viability of NATS using a photo-realistic environment created in the Unreal Engine 4 game development platform with the AirSim plugin.

I. INTRODUCTION

Active search (also called active sensing or target detection in robotics) refers to the problem of locating targets in an unknown environment by actively making data-collection decisions and finds use in many robotics applications such as search and rescue, localization and target detection [1], [2], [3], [4]. While there is a large amount of research on localization and detection algorithms in the field of robotics, majority of these algorithms are simplified and do not consider the practical side of fielding real sensors on multiple robots such as applying real detection algorithms to their observations. For example, a basic SLAM (simultaneous localization and mapping) formulation focuses on the uncertainties of locations while abstracting the detection of objects [5], [6]. Similarly, common coverage planners produce only simplistic plans with an abstraction on the object detectors [7]. Other work such as search theory do consider uncertainty measures of false positive and false negative in their object detection rate [8], [9]. However, they assume simplified point-wise (coarse cells) sensing actions that do not support typical field sensor setups that use common cameras paired with detectors. Similarly, active learning methods such as adaptive compressed sensing [10], [11], Bayesian optimization [12], [13] and bandit-style algorithms [14], [15] contain sophisticated reasoning about uncertainty but use simplified sensing models.

When a real, autonomous, multi-robot team performs active search, its performance is driven by its ability to handle a number of other practical issues. The first is that its detector reports detections probabilistically, and its precision-recall curves degrade with distance between the object and the detector (depth). Its performance is further constrained by the field of view of the device as well as occlusions created by terrain or other obstacles in the scene. An efficient algorithm considering all these features will often start by choosing actions that offer wide views over great distances and will then need to consider the best way to follow up on uncertain detections. It will also consider what areas of the space have received insufficient observation, potentially because they are well hidden, and do the painstaking work of ensuring nothing is missed. To achieve the best quantitative performance, all these behaviors should emerge from quantitative optimization, not a heuristic specification of behaviors.

Finally, executing this optimization with multiple robots adds an additional challenge. While centralized planning is one approach to multi-agent settings, it is often not practical. Communication constraints have been highly discussed in robotics literature. As an example, [1] talks about search and rescue missions and how communication can be unreliable in such systems. [16] talks about formation of multiple robots in coordinated tasks with robust reaction to communication loss. [17] provides a survey of multi-robot coordination and why centralized coordination is not a practical assumption. As stated by [18] on multi-robot target detection: “Some papers do mention the issues raised by the communications constraints, but hardly provide solutions.” To clarify, there must be at least some communication between agents to share information, otherwise they are just independent actors, not a team. However, a central coordinator that expects synchronicity is not feasible as any communication or agent failure could disrupt the entire process. We will assume agents do communicate their acquired measurements, yet each agent independently decides on its next sensing action using whatever information it happens to receive.

All these features are motivated by real world requirements such as the real multi-robot search team in [19] which includes decentralized autonomy in perception, navigation and path planning. However, they require an operator to dictate waypoints (goal locations) to robots. In this paper, we focus on developing an autonomous decentralized multi-agent active search method that performs waypoint selection while taking into account practical field sensing models such as detection depth uncertainty, field of view and terrain occlusions.
point-wise sensing actions where each point is a coarse cell area. Additionally, neither paper provide any insight on how to acquire this false positive probability nor do they relate it to sensor capabilities or target distance. Search theory methods in general focus on single-cell (point-wise) search where the environment is divided to a number of cells ([25], [26]). Such single-cell actions are not reflective of realistic sensors in open environments and can drastically increase search time ([27], [22], [28]). In this paper we make a realistic assumption that robots can observe multiple cells at each time step where our level of trust in each cell’s observation depends on their distance from the robot.

Another area of work that considers object localization is SLAM ([5], [6]). The traditional goal of SLAM is to provide localization for a robot by constructing a map of an unknown environment and localizing the robot in that map ([29]). Active search is slightly different since it assumes robot localization is provided (via SLAM or some other localization method) and its goal is locating objects of interest. Nonetheless, we can bring our attention to how SLAM literature manages sensor uncertainty. As an example ([30] and [31]) are monocular SLAM methods that try to localize the observer. They take into account the uncertainty of the location of features but are not concerned with uncertainty in their existence or finding objects of interest other than their use as localization features.

The computer vision (CV) literature has long explored ways of more efficiently finding objects in images, such as ([32], [33]). Their work continues to evolve ever more efficient deep learning based detectors, but it solves the problem of efficiently identifying object pixels within an image. Contrarily, we are interested in the problem of efficiently choosing images to physically locate objects of interest. The CV literature also contains significant work on uncertainty of detection and location of objects within an image ([e.g. [34], [35]]) which again does not translate into physical localization.

The Multi-Autonomous Ground robotic International Challenge (MAGIC) was a contest held in 2010 that closely matches the task we address in this work ([36], [37]). The main difference was that the participants were required to solve the SLAM problem as well and thus performed object detection as an extension of SLAM rather than developing efficient algorithms to find objects in the face of uncertain sensing given an existing ego-localization functionality.

A similar line of work uses MCMC to represent uncertainty in the map including uncertainty about the existence of features ([38]). Although they do reason about uncertainty in the existence of features, the driving goal is localization, not efficient discovery of objects of interest. ([39]) is a single-agent path planner that uses Monte Carlo Tree Search to choose the most informative path in terms of object classification assuming it was given a goal travelling location. Our problem formulation is focusing on finding out the goal locations. There is another area of work in search and pursuit-evasion ([40]) which is not the focus of this paper as they deal with a different application where targets are evading capture.

Finally, we introduce ([41]) which develops an info-greedy approach to locate moving targets. This reference is the only work we have seen in our extensive literature review that
includes a notion of object distance uncertainty in their search algorithm. In particular, they consider the number of pixels of an object as a parameter in their posterior distribution which can be translated to object’s depth uncertainty. However, their proposed info-greedy method is computationally so expensive that they made their action space binary to be able to get a closed form solution. Additionally, their multi-agent decision process is only sequential resulting in their algorithm’s complexity multiplying with the number of robots. Instead, our proposed NATS allows independent decision making for each robot and consequently its complexity is not affected by the number of agents.

C. Notation

Lowercase and uppercase boldface letters represent column vectors and matrices, respectively. For a matrix $A$, the transpose is $A^T$, and the $i$th row and $j$th column entry is $[A]_{i,j}$. For a vector $a$, the $i$th entry is $[a]_i$ or $a_i$. The $\ell_2$-norm of $a$ is $\|a\|_2$; $\text{diag}(a)$ is a square matrix with $a$ on the main diagonal, and the trace operator is $\text{tr}(\cdot)$.

II. DEPTH-AWARE SENSING MODEL

A. Problem Definition

Consider the gridded area in Figure 1a to be an area of interest for the active search mission where the marks “X” show the location of the objects of interest (OOI). Multiple ground robots are sent to the environment to locate said OOIs as fast as possible. Each robot moves around and senses its surrounding environment by taking a picture and passing it through a state of the art object detector, e.g. YOLOv3 of [42]. The red, yellow and blue triangles in this figure illustrate the sensing actions of each robot for a camera with a field of view of 90 degrees. As discussed in the introduction, robots do not have access to a central control unit to collectively decide where to sense next. As a result, each robot must independently decide on their next sensing action given their current belief of the location of the OOIs. While there is no central control unit, we assume that all robots constantly share their measurements with each other.

Once a robot senses a region, it will run the sensed image through an object detector. The object detector will extract objects that are likely to be OOIs with a given confidence measure. In general, for objects that are farther away from the camera, the probability of correctly identifying them with the detector is lower. We can measure this probability for a given object detector using training data. Our objective is to utilize this measure of uncertainty for each robot’s observation as a function of their distance from the camera. This uncertainty measure can help the robot with making sensing decisions. In particular, once a robot senses a region, given its uncertainty measure the robot can decide whether to go closer to better sense the region or to move on to other regions that are more likely to include an OOI. We will provide a model for this uncertainty measure in the next section.

We hereby note that we are not in any way replacing the localization and mapping portion of robot autonomy. We assume the robots are able to localize themselves. Our goal is to help making the tactical decisions on the next waypoints (sensing action) at each time step. In particular, we use Figure 2 to illustrate a simplified architecture of our autonomous robot. Our objective is to develop an algorithm for the dashed red box on tactical decision making.

B. Depth-Aware Modeling of an Object Detector

We intend to formulate the performance of an object detector with an additive noise model. Let us assume $\beta_i$ is the output of an ideal object detector that identifies object $i$ that is a distance $\ell_i$ away from the camera with either a “0” (not OOI) or a “1” (OOI). An imperfect object detector can sometimes misclassify the OOI with a false positive or a false negative. Therefore, one way to model the performance of the object detector is to model the misclassifications with an appropriate noise distribution such as Gaussian distribution with its variance describing the false positive and false negative rate. While this model is reasonable, it is disregarding an important piece of information on the confidence measure (accuracy) of the object detector. In general, when the object detector makes a mistake, we expect it to generate a lower accuracy measure [43]. In fact, we make the following claim:

Claim 1. We expect the accuracy measure of an object detector to gradually decline as a function of object’s distance from the camera.

In Section IV we provide a dataset to back up this claim for YOLOv3 object detector using images from a realistic environment we have created in Unreal Engine 4 editor. Using Claim 1, we will model the performance of the object detector by formulating its accuracy with an additive one-sided Gaussian noise as depicted in Figure 3. Precisely, for any given distance $\ell$ we assume an additive noise model $y_i = \beta_i + n_i$, where $n_i \sim \mathcal{N}(0, \sigma_i^2(\ell))$. The noise variance $\sigma_i^2(\ell)$ is a function of distance and increases the further the OOI is from camera.
C. Problem Formulation

We describe the mission environment (the gridded environment in Figure 1a) with a sparse matrix $\mathbf{B} \in \mathbb{R}^{n_1 \times n_2}$ with $k$ non-zero elements at the location of OOIs. We can consider each element of matrix $\mathbf{B}$ as the output of the perfect object detector with accuracy 0 for “no OOI” and accuracy 1 for “OOI”. Defining $\beta \in \mathbb{R}^n$ as a flattened version of matrix $\mathbf{B}$ with $n = n_1 \times n_2$, we can write the sensing operation for each agent at time step $t$ as follows:

$$y_t = \mathbf{X}_t \beta + \mathbf{n}_t, \quad \mathbf{n}_t \sim \mathcal{N}^+(0, \Sigma_t). \quad (1)$$

Here, matrix $\mathbf{X}_t \in \mathbb{R}^{d \times n}$ describes the sensing matrix at time $t$ (colored triangles representing the robot’s field of view (FOV)). To better describe the sensing matrix $\mathbf{X}_t$, consider Figure 1a. Essentially, each row of the sensing matrix $\mathbf{X}_t$ is a one-hot vector pointing out the location of one of the colored grid points inside the robot FOV triangle. We will discard entries of this FOV grids that are unavailable due to occlusion. We assume there are $d$ FOV grid points available at time step $t$. Next, $y_t \in \mathbb{R}^d$ is the observation vector modeling the output of an imperfect object detector as an accuracy measure. $\mathbf{n}_t \in \mathbb{R}^d$ is the depth-aware additive noise that is modeling the imperfect object detector as in Figure 1a from previous section. Specifically, for each of the $d$ grid points in the robot’s FOV, we consider their observations $[y_{t1}, \ldots, y_{td}]$ to be corrupted with independent additive Gaussian noises $[n_{t1}, \ldots, n_{td}]$ with their variance $\sigma_1^2, \ldots, \sigma_d^2$ a function of the grid point’s distance $(\ell_1, \ldots, \ell_d)$ from the robot. Consequently, the noise variance $\Sigma_t$ is a diagonal matrix with each of its entries referring to the noise variance for the corresponding FOV grid points, i.e. $\Sigma_t = \text{diag}(\sigma_1^2(\ell_1), \ldots, \sigma_d^2(\ell_d))$.

Remark 1. Note that since the focus of our algorithm is to provide goal locations for each agent (not to plan a continuous path), we only need a very coarse discretization for our environment. For example, in Section IV we will use grid sizes of $30 \times 30m$ to cover a $500 \times 500m$ area.

To best estimate $\beta$ and actively locate OOIs, at each time step $t$, we choose a sensing action $\mathbf{X}_t$ given all the available measurements thus far in the measurement set $\mathbf{D}_t$. Let us assume the overall number of measurements $(\mathbf{X}_t, y_t)$ available to all agents are $T$. Our objective is to estimate the sparse vector $\beta$ with as few measurements $T$ as possible. For a single agent, this procedure is sequential with the data sequence $\mathbf{D}_t = \{(\mathbf{X}_1, y_1), \ldots, (\mathbf{X}_{t-1}, y_{t-1})\}$. For a multi-agent setting, we use an asynchronous parallel approach with multiple agents independently making data-collection decisions as proposed in [44]. Precisely, as illustrated in Figure 1b, the asynchronicity means that the agents will not wait on results from other agents; instead, an agent starts a new sensing action immediately after its previous data acquisition is completed using all the measurements available thus far. As an example, the second agent in the multi-agent example in Figure 1b will start task 6 before tasks 4 and 5 are completed with $\mathbf{D}_t = \{(\mathbf{X}_t, y_t)| t \in \{1, 2, 3\}\}$.

III. Our Proposed Algorithm

As detailed in the introduction, we are interested in a multi-agent active data collection algorithm that locates sparse targets without the need for a central planner. We can classify this problem as an active learning algorithm with parallel computing setting [45]. Unfortunately, such algorithms are in general Batch-mode algorithms aiming at simultaneously solving for a batch of queries to be evaluated by all agents ([46], [47], [48]) and therefore require a central planner to coordinate between agents at all times. Another popular solution to active search is the use of entropy and information greedy methods. However, such algorithms ([12], [49], [2], [41]) are not adaptable to decentralized and asynchronous (non-sequential) multi-agent settings. In particular, if we were to use multiple agents with an info-greedy decision-making process, all agents would have made the same decision at each time step wasting resources of other agents. We will provide comparisons of such methods in our simulation results in Section IV. We will next propose our solution.

A. Thompson Sampling for Active Search

In [3], we proposed a parallelized Thompson Sampling algorithm for active search called SPATS that allows agents to make independent and intelligent decisions asynchronously on their sensing actions in the absence of a central planner. However, the proposed SPATS algorithm is limited to a simplified sensing action that entirely ignores the presence and effects of object detection and is more suited for unmanned aerial vehicles. In this section, we will use parallelized Thompson Sampling to develop an active search algorithm for the problem in Section II.

Thompson Sampling (TS) is an online optimization algorithm originally proposed in 1933 by [50] for a two-armed bandit problem rising in clinical trials. The idea of TS is to balance between exploration and exploitation by maximizing the expected reward of its next action assuming that a sample from the posterior is the true state of the world [51]. TS is an excellent candidate for an asynchronous multi-agent online algorithm without central planner. Essentially, by using a posterior sample in its reward function, TS allows a calculated randomness in the reward that enables multiple agents to independently solve for different values that equally contribute to the overall goal of estimating parameter $\beta$.

Having attracted a lot of attention in the past decade, TS has been successfully adapted to a variety of online learning problems [51]. Our active search problem falls in the category of parameter estimation in active learning as developed in [52] with the name Myopic Posterior Sampling (MPS). Similar to MPS, our goal is to actively learn (estimate) parameter $\beta$ by taking as few measurements as possible. For the sake of similarity, we will use TS to refer to MPS.

To perform active search, traditionally people have used coverage planning methods with exhaustive search ([53], [54], [55]). However, with the availability of observations with high and low uncertainty, an optimized active search method can locate OOIs faster than exhaustive search in terms of number of measurements (see Section IV for examples). Such faster recovery is achievable due to the concept of compressed sensing (sparse signal recovery) which says that we can recover a sparse signal with size $n$ by taking less than $n$ measurements with low or high resolution [56], [57]. By using compressed sensing with TS, we can create the right balance...
between exploring unknown regions with large uncertainty and then exploiting the ones we suspect of including an OOI with a closer look (lowering their uncertainty).

B. Developing NATS (Noise-Aware Thompson Sampling)

We will now derive the TS algorithm with sparse prior for each agent. Once an agent finishes an observation task, it will use all the available measurements to that agent at that point \( D_t \) to start a new sensing operation as follows.

Recall our interest in estimating parameter \( \beta \) in (1). We will now describe the process to choose sensing action \( X_t \) at time step \( t \) using TS. Assuming a prior \( p_0 \) for this vector and given the likelihood function \( p(y_t|X_t, \beta) = \mathcal{N}(X_t/\beta, \Sigma_t) \) for all previous measurements \( (X_t', y_t') \in D_t \), we can compute the posterior distribution as

\[
p(\beta|D_t) = \frac{1}{Z} p_0(\beta) \prod_{(X_t', y_t') \in D_t} p(y_t'|X_t', \beta).
\]

By taking a sample from this posterior \( \beta \sim p(\beta|D_t) \), sensing action \( X_{t+1} \) is chosen by maximizing a reward function that pretends \( \beta \) is the true beta. Specifically, we will use the reward function \( R(\beta, D_t, X_{t+1}) = -E_{y_{t+1}|X_{t+1}, \beta} \left[ \| \beta - \beta(D_t \cup (X_{t+1}, y_{t+1})) \|_2^2 \right] \), where \( \hat{\beta}() \) is our estimate of parameter \( \beta \) at time step \( t \) given all available measurements in \( D_t \cup (X_{t+1}, y_{t+1}) \).

To apply TS as described above, we need to choose a prior distribution \( p_0() \) for the vector \( \beta \) to compute its corresponding posterior. Since \( \beta \) is sparse with an unknown number of non-zeros, we use sparse Bayesian learning (SBL) originally proposed by [58] as our probabilistic model. We choose SBL for multiple reasons as pointed out by [59]. First, in many cases SBL have shown to achieve more accurate recovery results than \( \ell_1 \)-norm based regularization methods [60], [61], [59], second, SBL framework uses a simple Gaussian-based probabilistic model that makes computing the TS reward function process simpler, and third, SBL framework allows for tuning the unknown sparsity rate parameter \( k \) to be learned automatically through an Expectation-Maximization process. We now briefly discuss the SBL framework.

We place a zero-mean Gaussian prior over entry of vector \( \beta \) as in \( p(\beta_i) = \mathcal{N}(0, \gamma_i) \), with variances \( \gamma_i \) as hyperparameters \( (i = 1, ..., n) \). Since a Gaussian distribution does not impose sparsity, SBL framework introduces sparsity by choosing variances \( \gamma_i \) appropriately given measurements. Essentially, SBL chooses very small values for \( \gamma_i \) imposing sparsity unless compelling evidence proves a non-zero entry. Using this Gaussian prior along with our Gaussian likelihood \( \prod_{(X_t', y_t') \in D_t} p(y_t'|X_t', \beta) \), the posterior distribution in (1) is simply a Gaussian distribution \( p(\beta|D_t) = \mathcal{N}(\mu, \Sigma) \) with

\[
\Sigma = (\Gamma^{-1} + X^T \Sigma X)^{-1} \quad \& \quad \mu = VX^T \Sigma_y.
\]

Here, \( \Gamma \) is a diagonal matrix of all hyperparameters \( [\gamma_1, ..., \gamma_n] \); matrices \( X \) and \( \Sigma \) are a collection of all measurements in \( (X_t', y_t') \in D_t \) and variance \( \Sigma \) is a diagonal matrix containing their corresponding depth-aware noise variance. Since our posterior distribution is Gaussian, taking posterior samples for TS is not expensive.

Next, using a conjugate inverse gamma prior for hyperparameters \( \gamma_i \) as \( p(\gamma_i) = \mathcal{I}(a_i, b_i) = \frac{b_i^{a_i}}{\Gamma(a_i)} \gamma_i^{-(a_i-1)} e^{-b_i/\gamma_i} \), SBL optimizes these parameters by applying an expectation-maximization [58], [62]. With \( \beta \) as the hidden variable, the expectation step follows that of (3), while the maximization step is given by maximizing the likelihood \( p(y|\Gamma, X) = \int p(y|X, \beta) p(\beta|\Gamma) d\beta \) which compiles to:

\[
\gamma_i = (|V|)^{1/2} + [\mu_i^2 + 2b_i]/(1 + 2a_i).
\]

Lastly, using \( \mu \) in (3) as the posterior mean estimate for \( \beta(D_t \cup (X_{t+1}, y_{t+1})) \), it is straightforward to compute the reward \( R(\beta, D_t, X_{t+1}) \) for TS at time step \( t + 1 \) as follows.

\[
R(\beta, D_t, X) = \mathbb{E}_{y_{t+1}|X_{t+1}, \beta} \left[ -\|eta - \hat{\beta}(D_t \cup (X_{t+1}, y_{t+1}))\|_2^2 \right] = -\|VX^T \Sigma y - \hat{\beta}\|_2^2 - 2\langle VX^T \Sigma y - \hat{\beta} \rangle^T VX^T \Sigma_{t+1} \hat{\beta}.
\]

Given the practical constraint we put on feasibility of sensing actions (colored triangles in Figure [14]), there is no closed form solution to optimize for the reward (5). Consequently, we will have each agent consider a group of feasible sensing actions in a fixed radius surrounding the agent’s current location. This strategy has two great benefits for us. First, our algorithm is taking into account travelling distance costs for each agent which is extremely important. Second, the size of the environment will not affect the optimization search size. Algorithm 1 summarizes our proposed NATS.

Algorithm 1 NATS

Assume: Sensing model (1), sparse signal \( \beta \), \( g \) agents
Set: \( D_0 = \emptyset \), \( \gamma_m = 1 \)
For \( t = 1, ..., T \)
   Wait for an agent to finish; for the free agent:
      Sample \( \beta \sim p(\beta|D_t, \Gamma) = \mathcal{N}(\mu, V) \) from (3)
      Select \( X_{t+1} = \arg\max_X R(\beta, D_t, X) \) using (5)
      Observe \( y_{t+1} \) given action \( X_{t+1} \)
      Update \( D_{t+1} = D_t \cup (X_{t+1}, y_{t+1}) \)
      Estimate \( \Gamma = \text{diag}(\gamma_1, ..., \gamma_n) \) using (4)

IV. EXPERIMENTAL RESULTS

A. Synthetic data

We now compare the performance of our NATS algorithms against 5 other methods in a synthetic setup. 1) An information-theoretic approach called “RSI” proposed in [2] that we have extended to multi-agent systems. RSI is a single agent active search algorithm that locates sparse targets while taking into account realistic sensing constraints. 2) In order to understand the role of sparsity in our algorithm, we will compare NATS to a similar TS algorithm that uses a simple Bernoulli prior \( p(\beta_i = 1) = k/n \) and \( p(\beta_i = 0) = 1-k/n \). We call this algorithm “BinTS” (for Binary TS) and assume it has perfect knowledge of sparsity rate \( k \). 3) A random algorithm we call “Rnd” which randomly chooses sensing actions at all times. 4) A point-sensing method we call “Point” that exhaustively searches the entire environment (exhaustive search). 5) An information-greedy approach we call “IG” (for
Information Gain) that computes information gain using the negative entropy of the posterior in $I(\beta)$. Consider a search environment with $n_1 \times n_2 = 16 \times 16$ grid points. We send $g$ agents over to actively search the environment to recover vector $\beta$ which is randomly generated using a uniform sparse prior with $k$ non-zero elements with value of 1. We assume agents can only be placed at the center of these grid points looking in 4 possible directions of North, South, East and West with fields of view of 90$^\circ$. In each direction, a total of 12 grid points are visible; 2 closest to the agent and 6 furthest away forming a pyramid shape. We assume there are no occlusions in this synthetic experiment, i.e. every time an agent makes a sensing action, it will receive 12 observation points (unless the robot is measuring the borders of the environment in which case it is less than 12). To simplify the setup, instead of creating a unique object detection noise distribution for each grid point, we will assume that at each direction the sensing actions are affected by three different levels of noise given their projection distance to the plain parallel to the agent’s location. For our simulations, we use three noise variance levels of $\{0.005, 4 \times 0.005, 9 \times 0.005\}$.

Figure 4a and Figure 4b show the results of full recovery rate as a function of number of measurements over random trials. In particular, we vary the number of measurements $T$ and compute the mean and standard error of the full recovery rate over 40 random trials. The full recovery rate is defined as the rate at which an algorithm correctly recovers the entire vector $\beta$ over the random trials. Here, $T$ includes the total number of measurements collected by all 4 agents. From these two figures we see that NATS significantly outperforms Point, BinTS, Rnd and IG for both sparsity rates. Here, outperforming BinTS is an evidence on the importance of sparsity that NATS takes into account. Meanwhile, low performance of IG confirms our discussion in Section III that info-greedy methods are not suitable for decentralized and asynchronous multi-agent settings due to lack of randomness in their reward function. We also see a performance comparison between NATS and RSI as follows. In Figure 4a with $k = 1$, we see that even though RSI is an info-greedy method, its performance is comparable to NATS. The reason for this contradicting behavior is that RSI is designed for $k = 1$, therefore its performance is so close to optimal (binary search) that it reaches recovery rate of 1 before the multi-agent system can negatively affect it. On the other hand, for higher sparsity rate of $k = 5$, RSI’s performance is largely declined. This is a result of first poor approximation of mutual information for $k > 1$ by RSI and second lack of randomness in its reward. Additionally, RSI uses a sensing model that is not suitable for incorporating object detection accuracy measures and its posterior calculations are highly complex in our simulations.

To further demonstrate the performance of NATS, we provide Figure 4c and Figure 4d. Figure 4c shows how all methods perform in terms of time as we increase the number of agents for $k = 5$. Specifically, we are plotting the time required for each algorithm to reach a minimum full recovery rate of 0.7 for different number of agents $g$. Here, time is defined as the average number of measurements each agent will be collecting in a multi-agent settings, i.e. $T/g$. In an optimal setting, we expect a single agent algorithm’s performance to multiply by $g$ as we increase the number of agents. We see that for all algorithms except for IG and RSI, the performance multiplies by $g$. As we increase the number of agents beyond 6, the performance improvement reaches incremental levels since we are getting closer to maximum performance. Info-greedy method of IG does not improve with agents as without randomness in its reward, all agents are taking the same action (Section III). Lastly, since RSI’s performance never reached full recovery rate of 0.7 for a $k = 5$, its performance plot is excluded from this figure. Lastly, in Figure 4d we plot time performance of all algorithms to reach a minimum full recovery rate of 0.5 in terms of their sparsity rate $k$. Here, we see that NATS is a very robust algorithm hardly affected by sparsity rates. As expected, Rnd has a harder time recovering all target as we increase $k$. On the other hand, since BinTS is designed for non-sparse vectors, its performance improves with sparsity rate $k$. Similar to Figure 4c, RSI’s performance is so weakened for any $k > 1$ that its recovery rate never exceeds 0.5.

### B. Unreal Engine

We test NATS in a photo-realistic environment using the Unreal Editor 4 (UE4) game development platform [63] with the Airsim plugin [64]. The UE4 platform allows the construction of different terrains and environments as well as the placement of objects within the environment. The Airsim plugin provides a Python API that allows the traversal of a vehicle through the UE4 environment. Airsim also allows collection of in-game data, such as first-person perspective screenshots of the environment and depth maps. Depth maps illustrate the distance between the camera and all objects in the environment. These screenshots plus depth maps simulate the collection of data from monocular optical cameras and sonar depth tracking, two commonly available datasets in robotics applications [29], [31], [30], [65]. Our UE4 environment
Fig. 6: (left) Topography of the UE4 game environment is shown in color with the coarse 30x30m grid overlain in white. (right) The percentage of each coarse grid that is visible to an agent located at -115 East, 25 North is shown as an example.

communications between agents in a decentralized way and is robust against communication disruptions. NATS performance improves accordingly with its number of agents and its complexity is not affected by neither number of agents nor sparsity rate. Future work includes considering moving targets useful for applications such as stopping animal poaching. Finally, as part of an ongoing work, we intend to implement NATS on the real multi-robot search team in [19].

C. Mathematical Modelling of YOLOv3 Object Detector

To back up Claim 1 in Section II, we randomly placed a large number of people and animals in our UE4 environment. We then used AirSim generated about 100 image and depth maps from the created environment and checked the accuracy measure of YOLOv3 [42] using the original weights trained by COCO dataset [66]. Figure 5a shows an example of what the environment and images look like. Using this dataset, we created a normalized histogram as shown in Figure 5b of YOLOv3’s accuracy on detected objects given their distance from the camera. Figure 5b clearly supports our mathematical modeling in Figure 3.

D. Apply NATS to our Unreal Engine Environment

To test NATS’s performance in our UE4 environment, we place 6 different people randomly in the environment. Since the environment is mountainous, sensing actions performed by ground robots can be partially obstructed from view by the hilly topography. We convert the UE4 environment to a geocoded Digital Elevation Map (DEM) with 1m horizontal resolution (Figure 6). We then create a coarse resolution coordinate system of the DEM using grid nodes spaced 30m apart. The visible portions of the environment (i.e., the viewshed) for a 2m tall observer is calculated for all observation points in the coarse grid using the Geospatial Data Abstraction Library in [67].

We have included a video demonstration of NATS applied to our UE4 environment in [68]. As captioned in the video, NATS successfully locates the people in the environment. Our video clearly demonstrates NATS’s capability in getting closer to objects with low accuracy measures.

V. CONCLUSIONS

We have developed a new algorithm (NATS) for conducting active search using multiple agents that takes into account field sensor uncertainties. NATS does not need to know the number of objects of interest, it takes into account topography obstruction as well as travelling cost, it maintains

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