Automated Detection, Localization, and Registration of Smart Devices With Multiple Robots

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Abstract— **In this paper we examine the problem of detecting and localizing an unknown number of objects of interest using a small team of mobile robots. Such problems frequently arise in infrastructure inspection or smart building applications, where the number of objects of interest is not known a priori, though the type of object being sought out is known. This task is difficult because the data association, *i.e.,* the matching of measurements to targets, is unknown and the sensors are unreliable, *i.e.,* they experience false positive and false negative detections and are unable to uniquely identify and label individual targets. We utilize the Probability Hypothesis Density (PHD) filter to perform multi-target estimation, completely avoiding the need for any explicit data association while simultaneously estimating the number of objects and their locations. The team selects actions, generated over a range of length scales, that maximize the expected information gain given the current estimate of the object locations. This information gain is computed as the mutual information between the set of targets and the binary event of receiving no detections. This hedges against uninformative actions in a computationally tractable manner. We present a series of simulated experiments, validating the performance of the proposed framework using multiple sensor modalities.**

I. Introduction

Teams of mobile, location-aware robots have the potential to automate many real-time information gathering tasks, fusing local sensor data from multiple vantage points into a cohesive, global estimate of the state of the environment. These data collection services will become an important connection between cloud-based services and Internet of Things (IoT) devices [1], both of which are becoming increasingly prevalent. For example, mobile robots could locate and interact with smart sensors that cannot directly communicate with cloud resources [2], [3]. The number of these smart devices in an area may be unknown as new devices are installed or moved. We may need to identify, localize, and register smart wireless sensors and actuators to enable services in smart buildings. If these devices number in the 100s or 1000s, as will be the case in large office buildings, we want this process to be fully automated. This work can also be applied to other domains such as search and rescue, security and surveillance, or feature-based mapping, where a team is searching for a known object (*e.g.,* a victim trapped due to a natural disaster) but the number of such objects is not known at the outset of exploration.

The approach we take in this work most closely relates to the authors' previous work in [4]. We use the probability hypothesis density (PHD) filter from Mahler [5] to perform the multi-target estimation, without the need for any explicit data association. The resulting estimate is then used to make control decisions, selecting the joint action for the team that maximizes the mutual information between the set of targets and the binary event of getting no detections. This effectively hedges against uninformative actions in a computationally tractable manner. In our previous work [4], the control strategy is myopic, only considering a single future measurement for each robot. This leads the robots to get caught in information minima, which the robots escape by driving to a random location within the environment. This paper offers a significant improvement, allowing the team to plan multiple actions over a receding horizon. Furthermore, these actions are planned over a range of length scales, allowing the robots to repeatedly search in a small neighborhood or to take multiple measurements across the environment. This prevents the robots from getting stuck in information minima and completely avoids the need for random actions. We also introduce a novel criterion, based on the entropy of the multi-target distribution, to terminate the exploration when the team is sufficiently confident is their estimate of the targets. We validate the proposed strategy through a series of simulated experiments, with the robot team accurately and consistently estimating the number of targets and their locations within the environment.[1]

II. Related Work

Multi-target estimation problems pose a significant challenge compared to single-target estimation due to the problem of data association. This association is often unknown and difficult to solve, due to false positive (*i.e.,* measurements to objects not of the desired type) and false negative (*i.e.,* failing to detect targets) measurements as well as true targets entering and leaving the sensor field of view (FoV). Data association is often solved using heuristics, or by using the maximum likelihood association as in [7]. However, these approaches are often computationally intensive.

To perform the multi-target estimation, we use the probability hypothesis density (PHD) filter from Mahler [5]. This approach is based on the concept of a random finite set (RFS) and avoids explicitly solving for the data association by

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[1] An expanded version of this has been submitted [6].

averaging over all possible associations in the general Bayes filter [8]. The PHD filter tracks the first statistical moment of the distribution over RFSs, analogous to the mean estimator in the Kalman filter [9], and simultaneously estimates the number of targets and their locations within the environment. This mathematical framework is also used in the information-based control computations.

Information-based control is a common method used to drive robots to detect and localize targets. Hollinger et al. [10] use an information-based objective function to perform autonomous ship inspection with an AUV platform. Hoffmann and Tomlin [11] and Charrow et al. [12] use mutual information to localize a single target, with the latter tracking a moving target. Julian et al. [13] use mutual information to explore unknown environments with a team of robots, assuming limited dependence between robots to scale up to large teams. Charrow et al. [14] use mutual information to detect and localize an unknown number of targets, but with known data association. Ryan [15] uses information-based model predictive control, localizing and tracking a moving target with a small team of UAVs. See Mayne and Michalska [16] and Mayne et al. [17] for surveys of receding horizon and model predictive control. We apply these ideas to the active estimation problem.

There is limited work on active control for target localization with unknown data association. Ristic and Vo [18] and Ristic et al. [19] also use the PHD filter for estimation and use Rényi's mutual information to drive a single robot to localize an unknown number of targets. However this approach does not scale to multiple robots or to large numbers of targets, as the control equations involve a summation over all possible data associations. Dames et al. [20] use Shannon's information to track a small number of targets, but, because we do not assume that the target positions are independent, the approach does not scale well in the target cardinality.

III. Problem Formulation

We have a team of R robots exploring an environment E in search of targets. Robot r has pose q_t^r at time t and collects sets of local measurements, $Z_t^r = \{z_{1,t}^r, \dots, z_{m_t^r,t}^r\}$, which has m_t^r measurements. The size of these measurement sets varies over time, due to false positive and false negative detections and due to true targets entering and leaving the sensor FoV. The team seeks to determine the set of target locations, $X_t = \{x_{1,t}, \dots, x_{n,t}\}$, where each $x_{i,t} \in E$.

A. Random Finite Sets

The sets X and Z from above are realizations of random finite sets (RFSs). An RFS is a set containing a random number of random elements, *e.g.,* each of the n elements x_i in the set $X = \{x_1, \dots, x_n\}$ is a vector indicating the position of a single target, as shown in Fig. 1. See Mahler [8] for more thorough definitions of RFSs and the associated mathematics presented in this section.

The notion of integration over a space of sets requires care, as sets may have different cardinalities and cannot be added in the same manner as random vectors. The so-called *set integral* of a function $f(X)$ from sets to real-numbers is

$$\int f(X)\,\delta X = \sum_{n=0}^{\infty} \frac{1}{n!} \int f(\{x_1, \dots, x_n\})\,dx_1 \dots dx_n. \quad (1)$$

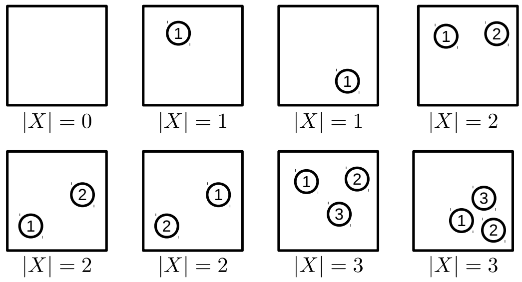

Fig. 1. Examples of random finite sets with 0 to 3 elements drawn from the square environment. The two sets in the lower left are identical, as sets are equivalent under permutations of their elements, *i.e.,* $X = \{1, 2\} = \{2, 1\}$.

Note the use of δ as the differential element in a set integral, and the outer sum over set cardinality. The $n!$ term accounts for the equivalence of a set under permutations of its elements.

The *probability hypothesis density* (PHD) is a density function over the state space of the targets, with the unique property that the integral of the PHD over a region S is the expected cardinality of an RFS X in that region. The PHD is also the first statistical moment of a distribution over RFSs. Note that it is *not* a probability density function, but may be turned into one by normalizing by the expected cardinality. We use $|\cdot|$ to denote set cardinality and $v(x)$ for the PHD.

Probability distributions over RFSs derive from point process theory. See Daley and Vere-Jones [21] for an overview of the subject. In deriving the PHD filter, Mahler assumes that RFSs have independently and identically distributed (i.i.d.) elements. The likelihood of such an RFS X is

$$p(X) = |X|!\, p(|X|) \prod_{x \in X} \frac{v(x)}{\langle 1,\, v\rangle}, \quad (2)$$

where the $|X|!$ term takes into account the permutations of set elements, $p(|X|)$ is the likelihood of the set cardinality, and the remaining terms are the likelihoods of targets being at the specified locations (*i.e.,* the normalized PHD at the target locations). The inner product between two real-valued functions a, b is

$$\langle a,\, b\rangle = \int_E a(x) b(x)\, dx,$$

or $\langle a,\, b\rangle = \sum_{k=0}^{\infty} a(k) b(k)$ for real-valued sequences.

B. Sensor Models

Each robot is equipped with a sensor, which may experience false negative or false positive detections, or return noisy measurements to true targets. The PHD filter framework requires models for each of these phenomena. The probability of a robot at q detecting a target with state x is denoted by $p_d(x; q)$ and is identically zero for all x outside the FoV. For each true target that is detected, the sensor returns a noisy measurement $z \sim g(z \mid x;\, q)$. The number and locations of false positive (or clutter) measurements is modeled by a PHD $c(z; q)$. Such clutter measurements may depend on environmental factors.

C. PHD Filter

The PHD filter tracks the first moment of the distribution over RFSs, providing a computationally tractable approximation to the Bayes filter. In this work, we assume that targets are stationary. To derive the PHD filter, Mahler [5] makes the additional assumptions that:

- the clutter and true measurement RFSs are independent;
- the clutter and predicted multi-target RFSs are Poisson.

The first assumption is standard for target localization tasks. However the second is less common within robotics. This assumption that set cardinalities follow a Poisson distribution stems from the use of Poisson point processes, which have the desirable property that the number of points in each finite region is independent if the regions do not overlap [21]. Letting the mean number of targets be $\lambda = \langle 1,\, v \rangle$, the target set likelihood (2) simplifies to

$$p(X) = e^{-\lambda} \prod_{x \in X} v(x), \tag{3}$$

and such an RFS is said to be Poisson.

The PHD filter update equation is

$$\begin{aligned} v_t(x) &= (1 - p_d(x; q)) v_{t-1}(x) \\ &\quad + \sum_{z \in Z_t} \frac{\psi_{z,q}(x) v_{t-1}(x)}{c(z; q) + \langle \psi_{z,q},\, v_{t-1} \rangle}, \end{aligned} \tag{4}$$

$$\psi_{z,q}(x) = g(z \mid x; q) p_d(x; q), \tag{5}$$

where $\psi_{z,q}(x)$ is the probability of a sensor at q receiving measurement z from a target with state x.

D. Mutual Information

Mutual information is a way to quantify the dependence between random variable $\mathcal{X}$ and $\mathcal{Z}$, and is defined as

$$\begin{aligned} I[\mathcal{X}; \mathcal{Z}] &= \iint p(X, Z) \log \frac{p(X, Z)}{p(X) p(Z)} \, dX dZ && (6) \\ &= H[\mathcal{Z}] - H[\mathcal{Z} \mid \mathcal{X}], && (7) \end{aligned}$$

where $H[\mathcal{Z}]$ is the entropy and $H[\mathcal{Z} \mid \mathcal{X}]$ is the conditional entropy of the measurements [22]. Throughout the paper, we use lowercase letters for realizations of random numbers and vectors (*e.g.,* x is the position of an individual target), capital letters for realizations of RFSs (*e.g.,* X is a set of target locations), and script letters for random variables (*e.g.,* $\mathcal{X}$ is the random variable representing target locations).

TABLE I

TABLE OF SYMBOLS

R	Number of robots	z	Measurement
q	Robot pose	Z	Measurement set
Q	Action set	y	Binary Measurement
x	Target pose	$p_d(x; q)$	Probability of detection
$v(x)$	Target PHD	$g(z \mid x; q)$	Measurement likelihood
λ	Expected # targets	$c(z; q)$	Clutter PHD
T	Time horizon	μ	Expected clutter rate
ϵ	Termination criterion		

IV. Information-Based Control for Automation

Mahler developed the PHD filter [5] as a tractable approximation to the general Bayes filter over RFSs. The Bayes filter is intractable, in part, due to the measurement likelihood term $p(Z \mid X)$ containing a sum over all possible data associations. The number of associations grows combinatorially in the number of measurements and targets. This same likelihood term appears in the expression for the mutual information between the target and measurement sets, necessitating another simplification. Instead of the full measurement set, we consider the event of receiving an empty measurement set. We represent this with the Bernoulli random variable $\mathcal{Y}$, where $y = 0$ indicates that the robot receives no measurements of any kind (*i.e.,* $Z = \varnothing$) and $y = 1$ indicates that to the robot receives at least one measurement.

In this paper, we extend the information-based control law from [4] to consider actions over a receding horizon, $\tau = \{t+1, \ldots, t+T\}$. Let $\mathcal{X}_{t+T}$ be the predicted target set at the end of the horizon and $\mathcal{Y}_\tau^{1:R}(q_\tau)$ be the collection of Bernoulli measurements for robots 1 to R over the horizon τ. These Bernoulli measurements depend on the future locations of the robots $q_\tau = [q_{t+1}^1, \ldots, q_{t+T}^1, \ldots, q_{t+T}^R]$ through the sensor models from Sec. III-B. The information-based control law is then

$$q_\tau^* = \operatorname*{argmax}_{q_\tau \in Q_\tau^{1:R}} I[\mathcal{X}_{t+T}; \mathcal{Y}_\tau^{1:R}(q_\tau)]. \tag{8}$$

A. Action Sets

In order to prevent robots from getting stuck in local information minima, the set of potential actions for the team, $Q_\tau^{1:R}$, must be sufficiently diverse. In our previous work [4], the robots escape these minima by driving to a random location within the environment.

We now take a more principled approach by extending the set of candidate actions to include paths at multiple length scales. Robots have the option to repeatedly measure the local neighborhood, *e.g.,* if there is high uncertainty in a nearby target, or to travel to more distant areas, *e.g.,* visiting previously unexplored regions. To generate actions, each robot r selects candidate points at the various length scales from its current pose q_t^r such that the candidate points are sufficiently separated from one another (*e.g.,* $> 1\,\mathrm{m}$ apart). The robots plan minimum length paths to these points using A* and interpolate these paths to get the T intermediate poses

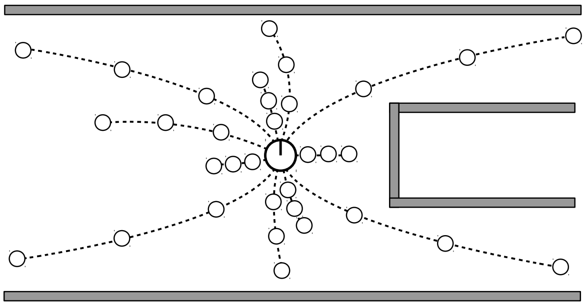

Fig. 2. Example action set with a horizon of $T = 3$ steps and three length scales. Each action is a sequence of T poses at which the robot will take a measurement, denoted by the hollow circles.

q^r_τ. The set of all such pose sequences form the action set for an individual robot, Q^r, shown in Fig. 2. Note that the number of steps, T, in each path is kept constant, regardless of the length scale, so that meaningful comparisons may be made between the information values of actions.

1) Concurrent: In our previous work, the team simultaneously considers all possible actions for all robots. In other words, the joint action set is the Cartesian product of individual robot action sets, *i.e.,* $Q^{1:R} = Q^1 \times \ldots \times Q^R$. The size of this joint action set grows exponentially in the number of robots, $|Q^{1:R}| = \mathcal{O}(|Q^r|^R)$, where $|Q^r|$ is the number of actions in an individual robot's action set. Such concurrent computations are prohibitively expensive for all but small teams of robots with small action sets.

2) Sequential: To reduce the computational load, the team may instead sequentially optimize actions for each robot. The first robot plans its action independently of all other robots and each subsequent robot selects an action conditioned on the actions of previous robots. The team repeats this process until reaching a consensus, *i.e.,* robots have a chance to update their original plans given the new plans of other robots. The sequence of joint action sets, $Q^{1:R}$, is

$$\begin{gathered} Q^1 \times \varnothing \times \varnothing \times \varnothing \times \ldots \times \varnothing \\ q^{*1} \times Q^2 \times \varnothing \times \varnothing \times \ldots \times \varnothing \\ q^{*1} \times q^{*2} \times Q^3 \times \varnothing \times \ldots \times \varnothing \\ \vdots \\ q^{*1} \times q^{*2} \times \ldots \times q^{*R-1} \times Q^R \\ Q^1 \times q^{*2} \times \ldots \times q^{*R-1} \times q^{*R} \\ q^{*1} \times Q^2 \times q^{*3} \times \ldots \times q^{*R} \\ \vdots \end{gathered}$$

where $q^{*r} \in Q^r$ has the highest expected information gain. This is similar to the idea of Adaptive Sequential Information Planning from Charrow et al. [14] and allows the team to consider many actions across many length scales.

In practice, the number of cycles until the team reaches a consensus is typically one, and never more than three. This approximation is not guaranteed to yield actions with the same information gain as concurrent planning, but it reduces the complexity to $\mathcal{O}(R|Q^r|)$.

3) Random: To validate the utility of intelligently selecting actions, we compare the proposed strategy to a controller that randomly selects actions from the joint action set.

B. Receding Horizon

In a receding horizon framework, robots replan their actions after executing only a fraction of their current action, here set to $1/T$ of the path length. Note that this is a fraction of the planned distance, so if one robot is acting at a much shorter length scale than the other robots, it may complete its entire action before the other robots complete $1/T$ of theirs. In this case, the first robot waits for the other robots to trigger the replanning.

C. Computing the Objective Function

We utilize the factorization of mutual information from (7) to compute the objective function in (8).

1) Entropy: The standard definition of entropy is

$$H[\mathcal{Y}] = -\langle p(y), \ln p(y) \rangle, \tag{9}$$

where there are 2^{RT} possible Bernoulli measurement combinations for R robots and T time steps. The task here is to compute the Bernoulli measurement likelihoods, $p(y^{1:R}_\tau)$, where we let $y = y^{1:R}_\tau$ for compactness.

The only way to get a Bernoulli measurement of 0 is to have no detections from true or clutter objects, so

$$p(y^r = 0 \mid X) = e^{-\mu} \prod_{x \in X} (1 - p_d(x_i; q^r)), \tag{10}$$

where $\mu = \langle 1, c \rangle$ is the expected number of clutter detections, $c(z; q^r)$ is the clutter PHD from Sec. III-B, and $e^{-\mu}$ is the probability of receiving no clutter detections given the assumption of Poisson clutter cardinality.

Let C_0 be the set of robots with $y^r = 0$ and C_1 the set of robots with $y^r = 1$. Then

$$\begin{aligned} p(y^1, \ldots, y^R) &= \int \left(\prod_{r \in C_0} p(y^r = 0 \mid X) \right) \\ &\qquad \times \left(\prod_{r \in C_1} 1 - p(y^r = 0 \mid X) \right) p(X) \, \delta X \\ &= \sum_{C \subseteq C_1} (-1)^{|C|} e^{-|C_0 \cup C| \mu - \alpha(C_0 \cup C) \lambda} \end{aligned} \tag{11}$$

$$\alpha(C) = 1 - \lambda^{-1} \left\langle \prod_{r \in C} (1 - p^r_d), \, v \right\rangle \tag{12}$$

where $\alpha(C)$ is the expected fraction of targets detected by at least one robot in group C.

2) Conditional Entropy: We use the standard assumption that measurements are conditionally independent given the target set, so

$$p(y^{1:R}_\tau \mid X) = \sum_{k \in \tau} \sum_{r=1}^{R} p(y^r_k \mid X). \tag{13}$$

Using this, the conditional entropy of the joint measurements becomes the sum of the conditional entropy of the individual measurements. For a single measurement, the expression is

$$\begin{aligned} H[\mathcal{Y} \mid \mathcal{X}] &= -\int \Bigg(\sum_{y\in\{0,1\}} p(y \mid X) \ln p(y \mid X) \Bigg) p(X)\,\delta X \\ &= e^{-(\lambda-\alpha\lambda+\mu)}(\mu+\lambda\beta) - \sum_{k=1}^{\infty} c_k e^{-(\lambda-\alpha(\{k\}^\ell)\lambda+k\mu)}, \end{aligned} \tag{14}$$

where $c_1 = 1$; $c_k = \frac{1}{k(k-1)}$ for $k = 2, \ldots, \infty$; $\{r\}^k$ is the set containing k copies of robot r; and

$$\beta = -\lambda^{-1} \langle (1-p_d)\ln(1-p_d),\, v\rangle\,. \tag{15}$$

The summation and coefficients c_k are a result of taking a Taylor series of $\ln$ about 0 in the $y = 1$ case. Note that $\alpha(\{r\}^k)$ may be computed using (12), and we use the first 10 terms in the Taylor series.

3) Computational Complexity: The complexity of the mutual information computations for a single action set is $\mathcal{O}(2^{2RT} + RT)$, where R is the number of robots and T is the planning horizon.

D. Exploration Termination Criterion

Deciding when to terminate the exploration is difficult when the number of targets is not known, as there could be targets outside of the visited area. Additionally, with the PHD filter there is no way to determine the team's confidence in the cardinality estimate, as the covariance is fixed by (and equal to) the mean by the assumption that the cardinality follows a Poisson distribution. Thus, we must assume that the team is able to accurately estimate the target cardinality, *i.e.,* $\lambda \to N$ as $t \to \infty$, where N is the true cardinality.

Ideally, the final PHD $v(x)$ will consist of N Dirac delta functions centered at the true target locations. Normalizing the PHD by the expected cardinality yields the probability density function of target locations, $\bar{v}(x) = \lambda^{-1}v(x)$, and the entropy of this distribution is $\log\lambda$. Such precision is not possible in practice, but the difference between the true PHD and this idealized case may be used to determine the team's confidence in the target estimate. The difference between the entropy of the current distribution and that of the ideal distribution appears in the expression for the entropy of a Poisson RFS [4],

$$H[\mathcal{X}] = \lambda + \lambda\big(H[\bar{v}(x)] - \log\lambda\big). \tag{16}$$

The proposed criterion is then,

$$\lambda^{-1}H[\mathcal{X}] - 1 \le \epsilon, \tag{17}$$

which terminates the exploration when the entropy of the target distribution is sufficiently close to the idealized version.

E. PHD Filter Implementation Details

In practice, the PHD is represented as a weighted set of particles, as in Vo et al. [23], or a Gaussian mixture, see Vo and Ma [24]. We use the particle representation, as it allows for nonlinear measurement models. Particles are initialized on a uniformly-spaced grid over the environment with equal weights, as we assume no a priori knowledge of target positions. Particles are also stationary since the targets are stationary. In this case, the complexity of the control objective (8) is $\mathcal{O}(|Q^{1:R}|P(RT + 2^{2RT}))$, where P is the number of particles in the PHD representation.

To reduce the computational complexity of the controller, we subsample the particles in the PHD by overlaying a uniform grid over the environment. All particles within a grid cell are merged into a super-particle with weight equal to the total weight of the merged particles and position equal to the weighted mean of the merged particles. This is similar to the idea from Charrow et al. [12].

V. Results

We conduct a series of simulation experiments to explore the performance of the proposed control strategy (8) in two smart building example scenarios: using bearing-only and range-only measurements to detect, localize, and register objects in an office building environment. Fig. 3a shows the test environment and the target locations, which are kept constant for all trials. The robots are modeled as kinematic, differential drive platforms and are set to match our experimental system [25].

A. Bearing-Only Sensors

Robots could receive bearing-only measurements from camera-based tracking systems, using image recognition software to detect known objects, *e.g.,* chairs, desks, waste bins, or doors in an office environment. In these simulated experiments the robot and sensor models are set to match our experimental system, where the robots are equipped with Hokuyo laser scanners and seek reflective targets in an indoor office environment [25]. Let $r(x,q)$ and $b(x,q)$ be the range and bearing of a point x in the local frame of the robot with pose q and let $\mathbf{1}(\cdot)$ be an indicator function. The detection model is given by

$$\begin{aligned} p_d(x;q) &= (1-p_{\text{fn}})\min\left(1, \frac{d_t}{r(x,q)\theta_{\text{sep}}}\right) \\ &\times \mathbf{1}\left(b(x,q)\in[b_{\min},b_{\max}]\right)\mathbf{1}\left(r(x,q)\in[0,r_{\max}]\right), \end{aligned} \tag{18}$$

where $p_{\text{fn}} = 0.210$ is the probability of a false negative, $d_t = 1.28\,\text{in}$ is the effective target diameter, $\theta_{\text{sep}} = 0.25°$ is the angular separation between beams in the laser scan, $b_{\max} = -b_{\min} = \frac{3\pi}{4}\,\text{rad}$ are the maximum and minimum angles, and $r_{\max} = 5\,\text{m}$ is the maximum range. The measurement model is

$$g(z \mid x;q) = \frac{1}{\sqrt{2\pi\sigma^2}}\exp\left(-\frac{\big(z-b(x,q)\big)^2}{2\sigma^2}\right), \tag{19}$$

where $\sigma = 2.25°$. The clutter PHD is

$$c(z) = \frac{p_u \mu}{b_{\max} - b_{\min}} \mathbf{1}\left(z \in [b_{\min}, b_{\max}]\right) + \frac{(1-p_u)\mu}{2\theta_c} \mathbf{1}\left(\big||z| - \pi/2\big| \leq \theta_c/2\right), \quad (20)$$

where $p_u = 0.725$ is the probability of a clutter measurement coming from the uniform component, $\theta_c = 0.200\pi\,\mathrm{rad}$ is the width of the peaks to the side of the robot (*i.e.,* at $\pm\frac{\pi}{2}$), and $\mu = 0.532$ is the expected number of clutter measurements per scan. The clutter cardinality distribution is Poisson with mean μ.

We wish to verify that the information-based strategy outperforms a naïve random walk and that the receding horizon planner outperforms the myopic search strategy. We test a team of three robots in four different planning configurations: sequential planning with multiple length scales and a time horizon $T = 3$, sequential planning with multiple length scales and a time horizon $T = 1$, sequential planning with a single length scale ($L = 1$) and a time horizon $T = 1$, and random planning. We give the robots a time budget of 900 s to complete the exploration task (with $\epsilon = 0.05$ in (17)). For each planning method, we perform ten trials.

Fig. 3 shows the results of the simulated experiments. Using any of the control strategies, the robots are able to accurately and consistently determine the target cardinality and locations. Robots using any variant of sequential planning complete the exploration task within the time budget in all ten trials. The robots using a receding horizon complete the task most quickly and consistently, with a median time of 291.8 s and a maximum time of 358.5 s. Robots using the myopic search over multiple length scales are also consistent, but the median time is noticeably higher at 433.2 s. Robots using the myopic strategy with a single length scale of 1 m, similar to our prior work [4], are less consistent and complete the task in a median time of 384.4 s. Robots using the random method only complete the task within the time budget in 2 of the 10 trials, with a minimum time of 864.1 s. Even though the random method is orders of magnitude faster at selecting actions, this does not counteract the fact that the actions are not being selected in an intelligent manner. The planning time for all of the methods is negligible compared to the total time of exploration, taking less than 1% of the time.

B. Range-Only Sensing

We also conduct a series of simulations where the robots are equipped with noisy, range-only sensors. This could be used, for example, to detect wireless smart sensors using the received signal strength. The parameters for the sensor in these simulations are not based on a specific physical sensor, but rather seek to capture the general behavior of an RF-based range sensor. Fig. 4b shows the detection model, $p_d(x; q)$. The measurements have zero-mean Gaussian noise, so $z \sim \mathcal{N}(|x - q|, \sigma^2)$, where $\sigma = 1\,\mathrm{m}$. The measurement noise is relatively high compared to the bearing-only sensor, so we expect the rate of information gain to be lower and localization to be less precise. Clutter detections occur uniformly over the range of the sensor, with a clutter PHD $c(z) = \mu/r_{\max}$, where $\mu = 0.1$ is the clutter rate and $r_{\max} = 5\,\mathrm{m}$ is the maximum range.

Most of the simulation parameters are kept constant: a team of 3 robots begins at location s in Levine, and uses sequential planning with a time horizon $T = 3$. The termination criterion is $\epsilon = 3$ to account for the much coarser localization that the range-only sensor is able to achieve, due to the high measurement noise, and the robots are given a time budget of 1200 s.

Fig. 4 shows the resulting completion times, cardinality estimates, and target set entropies, as well as an example localization result. As is expected, the system takes longer to complete the localization task, and the resulting target estimates are not as precise as with the bearing-only sensor. Despite the errors in target localization, the team is still able to accurately estimate the true target cardinality and to discover the approximate locations of all of the targets.

VI. Conclusion

In this paper we consider the problem of automating the detection, localization, and registration of an unknown number of objects using a team of mobile robots. These objects can be embedded sensors and actuators in smart buildings or targets of interest. The robots are equipped with unreliable sensors, which may fail to detect targets within the field of view, may return measurements to clutter objects, and are unable to uniquely identify individual targets. Examples of such sensing modalities include radio signal strength and object recognition using cameras. We use the PHD filter to perform multi-target localization, simultaneously estimating the number of targets and their locations despite the challenges in sensing. Additionally, our approach does not require any explicit data association, offering a significant computational advantage.

We propose a new receding-horizon, information-based control law to drive a team of robots to autonomously detect, localize, and register an unknown number of objects in a known map. This offers a significant improvement in performance compared to our previous work [4]. We completely eliminate the need for random control actions by considering actions across different length scales. We also extend the planning framework to consider multiple time steps by introducing an approximate planning method, sequentially planning over robots in the team. We conduct a series of simulated experiments, validating the performance of this approach with multiple sensing modalities. We also introduce a novel criterion for terminating the exploration task in the situation where the number of targets is unknown. Using our framework, the team is able to accurately determine the locations of all of the targets, without any clutter objects in the final estimate. Additionally, the team accurately and consistently estimates the target true cardinality, achieving both objectives of the exploration task.

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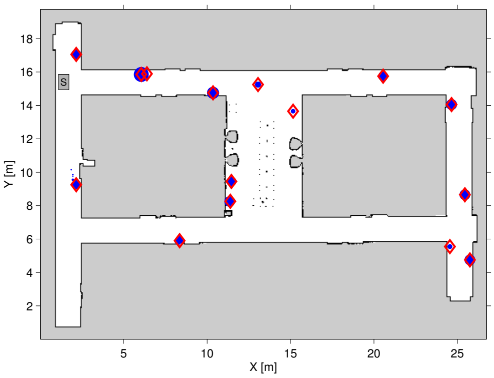
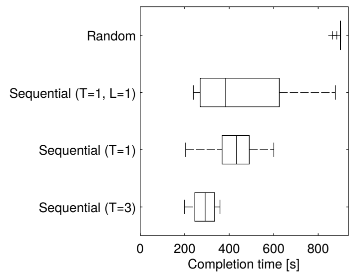
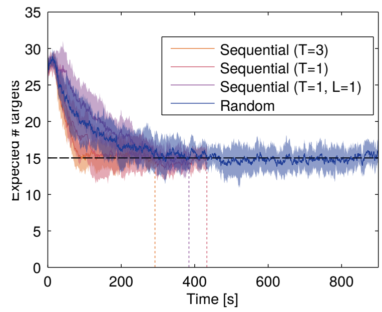


(a) Environment with example localization result



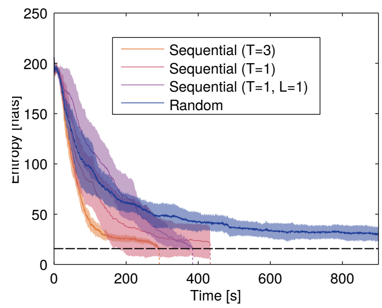
(b) Completion times



(d) Average expected cardinality over time

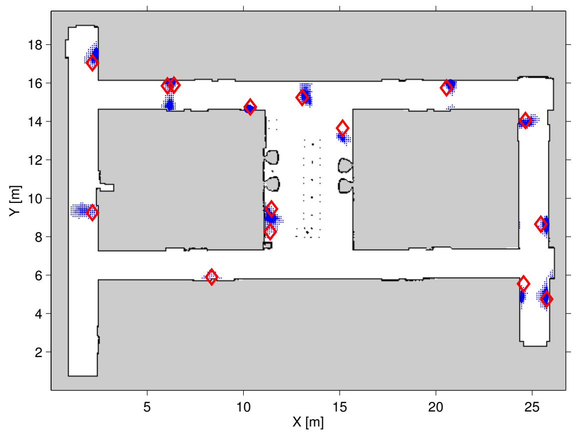
Planning method	Avg. time [ms]	Max time [ms]	% total time
Seq. ($T = 3$)	162	188	0.86%
Seq. ($T = 1$)	35.3	120.2	0.62%
Seq. ($T = 1, L = 1$)	12.2	54.8	0.23%
Random	0.3	0.4	0.002%

(c) Table of computation times

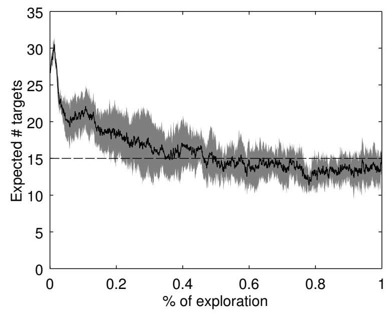


(e) Average target set entropy over time

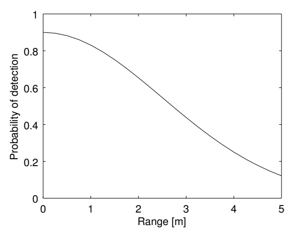
Fig. 3. Plots of the performance for a team of three simulated robots using sequential and random planning. (a) The environment, with the robots beginning at location s. An example localization result is overlaid, showing the true (red diamonds) and estimated target locations (blue dots), with the dot size proportional to the estimated number of targets at that location. (b) The statistics of the time needed to complete the exploration task. (c) The computation times of the control law in ms, and the percentage of the total time spent computing. (d) The mean (solid lines) and standard deviation (shaded regions) of the expected cardinality across over time, with the true value shown (dashed black line). (e) The mean (solid lines) and standard deviation (shaded regions) of the entropy over time, with the ideal value shown (dashed black line).



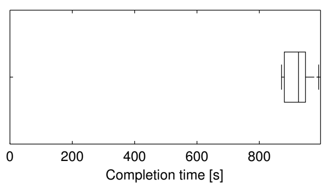
(a) Estimated target locations



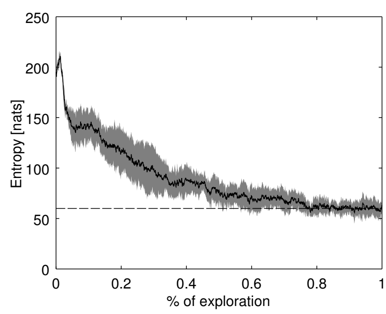
(d) Average expected cardinality as a function of normalized time



(b) Range-only detection model



(c) Completion times



(e) Average target set entropy as a function of normalized time

Fig. 4. Plots of the performance for a team of three simulated robots equipped with range-only sensors exploring the Levine environment using sequential planning with a time horizon $T = 3$. (a) Shows the true (red diamonds) and estimated (blue dots) target locations, with dot size proportional to the number of targets at that location. (b) Shows the detection model used in the simulation trials. (c) Shows the spread of time to completion. (d) Shows the mean (solid lines) and standard deviation (shaded regions) of the expected cardinality across runs as a fraction of the total time with the true cardinality shown (dashed black line). (e) Shows the mean (solid lines) and standard deviation (shaded regions) of the entropy across runs as a fraction of the total time with the ideal value shown (dashed black line).

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