Sensing, Predicting, and Planning: Robotic Expeditionary Science in Spatiotemporal Fields

by

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Submitted to the Department of Aeronautics and Astronautics
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Abstract

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Chapter 1

Introduction

The environmental sciences are a multidisciplinary endeavor to understand the Earth, its ecosystems, and its processes, for which *in situ* observational studies or *expeditions* serve as the foundation on which scientific discovery and model development is predicated. Robots are uniquely well-positioned to advance long-term monitoring of and exploration in meso-scale planetary environments through autonomous expeditions. By virtue of their form, robots can be used in extreme places (e.g., deep sea), dangerous scenarios (e.g., edge of calving ice sheets), or long-term missions (e.g., Mars exploration). Increasingly, robotic platforms are being developed for scientific expeditions, but their autonomous capabilities are typically limited to predetermined hand-designed trajectories (e.g., uniform coverage lawnmowers [Camilli et al., 2010]). This significantly restricts the class of phenomena that can be effectively studied by expeditionary scientific robots. For instance, spatiotemporal distributions—deep sea hydrothermal plumes, algal blooms, weather cells—can be severely under-sampled or missed using these strategies [Flaspohler et al., 2019]. Given the ubiquity of these spatiotemporal phenomena and the cost of scientific field operations, it is critical to improve the efficacy of robots as autonomous scientific tools.

This thesis represents. . .

Chapter 2

Problem Setting

To collect useful samples of a spatiotemporal field using a robotic platform is to pose a *sequential decision-making* problem. In this setting, we assume that the measurements that can be collected are partial observations of the unknown spatiotemporal environment, and the actions the robot can take in sequence are operationally constrained. We can formally state this problem as a partially observable Markoc decision process (POMDP). Let $\Pi(\cdot)$ denote the space of probability distributions over the argument. A finite horizon POMDP can be represented as tuple: $(\mathcal{S}, \mathcal{A}, T, R, \mathcal{Z}, O, b_0, H, \gamma)$, where $\mathcal{S}$ are the states, $\mathcal{A}$ are the actions, and $\mathcal{Z}$ are the observations. At planning iteration t, the agent selects an action $a \in \mathcal{A}$ and the transition function $T : \mathcal{S} \times \mathcal{A} \to \Pi(\mathcal{S})$ defines the probability of transitioning between states in the world, given the current state s and control action a. The transition function governs both how the state of the robot will evolve, given a chosen action, and the potentially stochastic evolution of the underlying spatiotemporal environment. After the state transition, the agent receives an observation according to the observation function $O : \mathcal{S} \times \mathcal{A} \to \Pi(\mathcal{Z})$, which defines the probability of receiving an observation, given the current state s and previous control action a. The reward function $R : \mathcal{S} \times \mathcal{A} \to \mathbb{R}$ serves as a specification of the task, assigning the states of the world that are useful for a given scientific objective high reward and others low reward. A POMDP is initialized with belief $b_0 \in \Pi(\mathcal{S})$ — an initial probability distribution over state — and plans over horizon $H \in \mathbb{Z}^+$ with discount factor

$\gamma \in [0, 1]$.

As the robot moves through the world, it selects actions and receives observations. Since the state of the world is not directly observable in a POMDP, the robot maintains a probability distribution over possible states (i.e., belief) and must update this distribution each time it takes an action and receives an observation. Given the transition and observation models, the belief can be updated directly using Bayes rule using a Bayes filter [Särkkä, 2013]:

$$\tau(b_{t-1}, a_{t-1}, z_t) = b_t \triangleq \Pi(S_t \mid a_0, z_0, \dots, a_{t-1}, z_{t-1}, z_t) \tag{2.1}$$

$$= \Pi(S_t \mid b_{t-1}, a_{t-1}, z_t) \tag{2.2}$$

$$= \frac{\int_{s \in \mathcal{S}} O(s, a_{t-1}, z_t) T(s, a_{t-1}, s') b_{t-1}(s')}{\Pi(z_t \mid b_{t-1}, a_{t-1})} \tag{2.3}$$

where $\tau(b, a, z)$ is the updated belief after taking control action a and receiving observation z (Eq. (2.3)). Unfortunately, Eq. (2.3) is intractable to compute directly and an approximate Bayesian inference procedure is required to represent the belief (e.g., Kalman filter [Welch et al., 1995], particle filter [Silver and Veness, 2010], or variational methods).

Due to the stochastic, partially observable nature of current and future states, the realized reward in a POMDP is a random variable. Optimal planning is defined as finding a horizon-dependent policy $\{\pi_t^* : \Pi(\mathcal{S}) \to \mathcal{A}\}_{t=0}^{H-1}$ that maximizes expected reward: $\mathbb{E}\left[\sum_{t=0}^{H-1} \gamma^t R\big(S_t, \pi_t(b_t)\big) \mid b_0 \right]$, where b_t is the updated belief at time t, conditioned on the history of actions and observations. The recursively defined horizon-h optimal value function V_h^* quantifies, for any belief b, the expected cumulative reward of following an optimal policy over the remaining planning iterations: $V_0^*(b) = \max_{a \in \mathcal{A}} \mathbb{E}_{s \sim b}[R(s, a)]$ and

$$V_h^*(b) = \max_{a \in \mathcal{A}} \mathbb{E}_{s \sim b}[R(s, a)] + \gamma \int_{z \in \mathcal{Z}} \Pi(z \mid b, a) V_{h-1}^*(\tau(b, a, z)) \, \mathrm{d}z \quad h \in [1, H-1], \tag{2.4}$$

The optimal policy at horizon h is to act greedily according to a one-step look ahead of

the horizon-h value function. However, Eq. (2.4) is intractable for large or continuous state, action, or observation spaces and thus the optimal policy must be approximated. Much of the art of practical decision-making uncertainty is making well-designed algorithmic and heuristic choices that enable efficient and robust planning algorithms.

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TRANSECT PAPER!

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Armadillos	are
our	friends

Bibliography

Camilli, R., Reddy, C. M., Yoerger, D. R., Van Mooy, B. A., Jakuba, M. V., Kinsey, J. C., McIntyre, C. P., Sylva, S. P., and Maloney, J. V. (2010). Tracking hydrocarbon plume transport and biodegradation at deepwater horizon. *Science*, 330(6001):201–204.

Flaspohler, G., Preston, V., Michel, A. P., Girdhar, Y., and Roy, N. (2019). Information-guided robotic maximum seek-and-sample in partially observable continuous environments. *IEEE Robotics and Automation Letters*, pages 3782–3789.

Särkkä, S. (2013). *Bayesian filtering and smoothing*. Number 3. Cambridge university press.

Silver, D. and Veness, J. (2010). Monte-Carlo planning in large POMDPs. In *Proc. Adv. Neural Inf, Process, Syst.*, pages 2164–2172.

Welch, G., Bishop, G., et al. (1995). An introduction to the kalman filter.