Autonomous Marine Sampling

Enhanced by Strategically Deployed Drifters in Marine Flow Fields

Johanna Hansen[1], Sandeep Manjanna[1], Alberto Quattrini Li[2,3], Ioannis Rekleitis[2] and Gregory Dudek[1]

[1]Mobile Robotics Lab at McGill University, {jhansen,msandeep,dudek}@cim.mcgill.ca
[2]Autonomous Field Robotics Lab at University of South Carolina, yiannisr@cse.sc.edu
[3]Department of Computer Science at Dartmouth College, alberto.quattrini.li@dartmouth.edu

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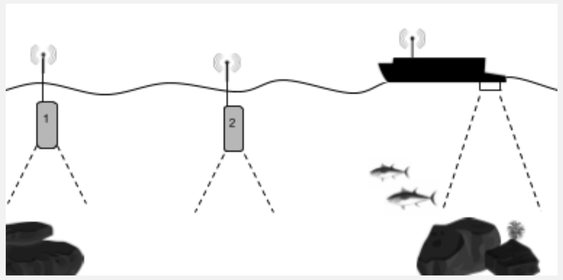
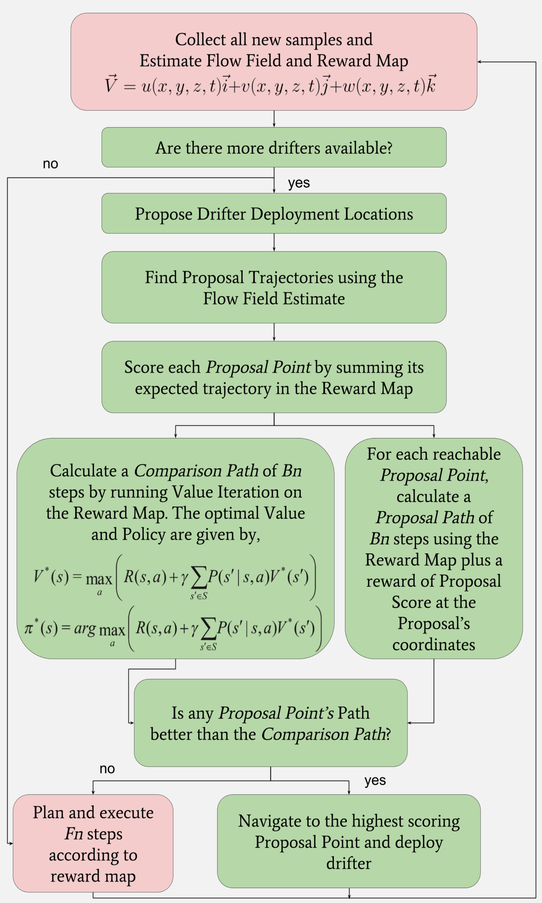
Introduction

We present a transportable system for ocean observations in which an autonomous surface vehicle (ASV) adaptively collects spatially diverse in-situ samples of marine phenomena and the flow field with aid from a team of strategically deployed, inexpensive, passive floating sensors known as *drifters*.

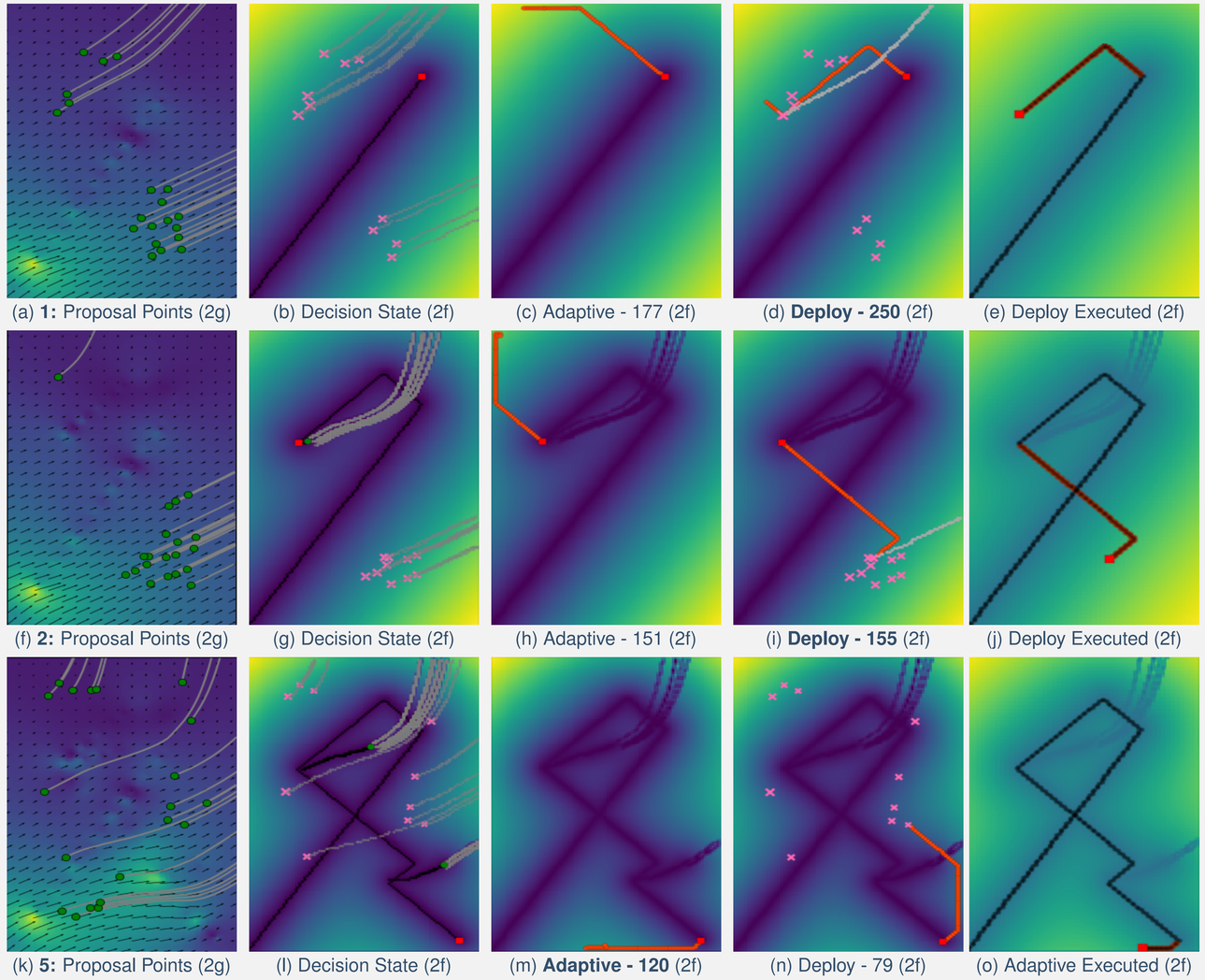


Sampling Approach

- At each iteration, begin by building a model of the flow field with uncertainty. We use a Gaussian Process [6] with an exponential kernel of the form: $K(a,a') = \sigma^2 \exp(\frac{(a-a')^2}{2l^2})$, with $\sigma = 1$, $l = 4$.



Survey Example

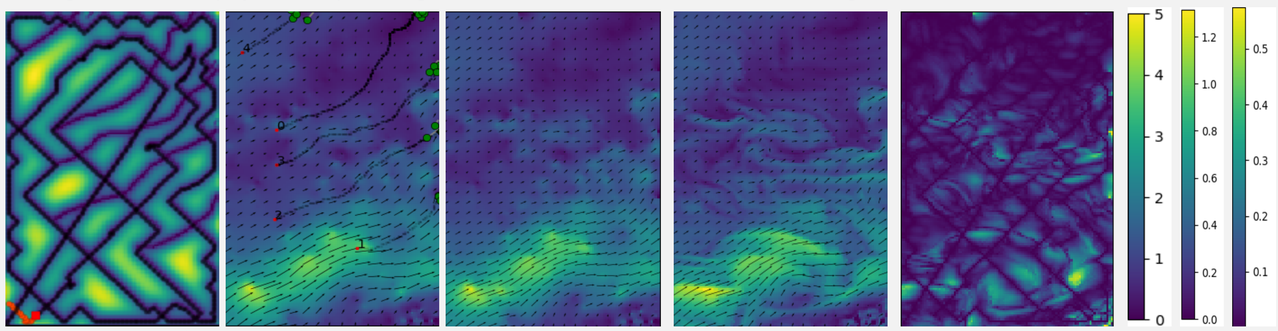


(a) **1:** Proposal Points (2g) (b) Decision State (2f) (c) Adaptive - 177 (2f) (d) **Deploy - 250** (2f) (e) Deploy Executed (2f)

(f) **2:** Proposal Points (2g) (g) Decision State (2f) (h) Adaptive - 151 (2f) (i) **Deploy - 155** (2f) (j) Deploy Executed (2f)

(k) **5:** Proposal Points (2g) (l) Decision State (2f) (m) **Adaptive - 120** (2f) (n) Deploy - 79 (2f) (o) Adaptive Executed (2f)

Figure 1: These panels show 3 decision points in a survey in which the ASV is attempting to estimate the flow field shown below in **Fig 2d**. Here the ASV replans every $F_n = 15$ steps and considers deploying one of its 5 drifters. The current estimate of the flow field at the numbered decision point is depicted in the background of the figures in the **Proposal Points** column. At each **Decision State**, we compare a hypothetical **Adaptive Path** of $B_n = 50$ steps to a drifter **Deployment Path** in which a drifter is deployed to the best **Proposal Point**. We choose the higher scoring trajectory as the next plan, with drifter path estimated using [1]. Below, in **Fig 2a**, we show the full boat path at the end of an experiment over the final model uncertainty and in **Fig 2b** we show deployed drifter paths. **Fig 2e** is the error from our flow field estimate in **Fig 2c**.



(a) Final Paths (2f) (b) Drifter Paths (2g) (c) Estimate (2g) (d) True Flow Field (2g) (e) Final RMSE (2h) (f) R (g) S (h) E

Figure 2: Survey Results

Results

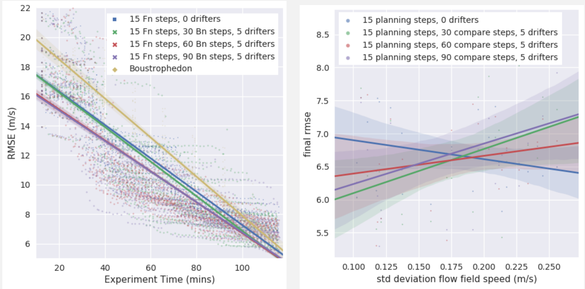
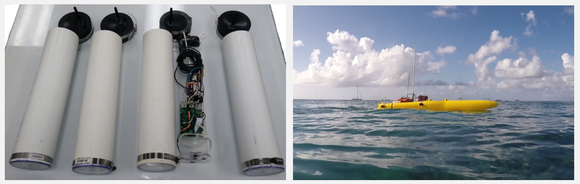


Figure 3: Plots show results over all 25 ROMS [8] flow fields tested. **Left:** The lines indicate RMSE at each point in survey time as data was assimilated. Our approach is able to accurately model the true data faster, though all schemes converge given enough time. **Right:** Final RMSE after the ASV sampled for 2 hours against flow field standard deviation. Our approach has higher performance when the flow field is more predictable (lower variance).



(a) Drifters (b) ASV

Conclusions

- We investigate *survey time, energy, and modeling error* and present a tunable algorithm for adaptive sampling with *strategic drifter deployment*.
- This work shows that by exploiting passive sensor platforms, we can *improve performance* in observation systems while only marginally increasing cost.

Acknowledgements

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