A Hierarchical Informative Path Planning Method for Ocean Monitoring

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I. Introduction

Ocean (environmental) monitoring and sensing allow scientists to gain a greater understanding of the planet and its environmental processes related to, e.g., physical, chemical or biological parameters. A key challenge of the environmental monitoring lies in the sensing, modeling, and predicting large-scale and spatially correlated environmental phenomena, especially when they are unknown and non-stationary [2]. In practice, many sensing applications require continuous information gathering in order to provide a good estimate of the state of the environment at any time [1].

We developed a path planning method that guides an autonomous underwater vehicle (AUV) to collect ocean data in the most efficient way. By efficiency we mean the "informativeness" of collected data (i.e., reduction of phenomena modeling uncertainty) as well as the minimization of energy and time used to collect the data. Such a planning framework is also called *informative path planning* [1].

We employ a Gaussian Process [4] to model an underlying phenomenon, and utilize the mutual information between visited locations and the remainder of the space to characterize the amount of information collected. Related to the practical ocean monitoring scenarios, we also consider the AUV's action uncertainty due to disturbances caused by the non-stationary ocean currents, and extend the Markov Decision Process [3] in continuous space to control AUV's motion.

We validated the method through extensive simulations with real ocean data and show that the method not only maximizes information-gain but also saves time and energy while exploring the non-stationary ocean.

II. Technical Approach

A. Environment Representations & Methodology Framework

To represent the ocean environment, we discretize the environment into a grid map. Each grid at a location stores a mean value that predicts the phenomenon interested as well as a variance that measures the uncertainty of such prediction.

We characterize the most informative regions by using a hierarchical structure, which is illustrated in Fig. 1. We recursively apply the information-driven planner to get new batches of observation points at finer resolutions. The process is repeated until the specified bottom layer of the hierarchy is reached.

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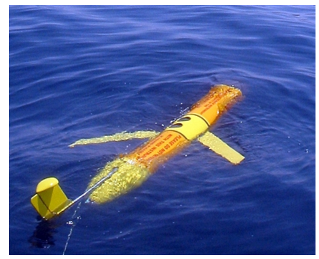
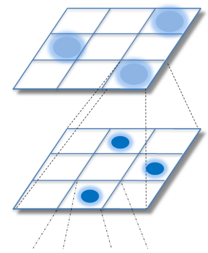


(a)



(b)

Fig. 1. (a) A Slocum marine glider used for ocean monitoring; (b) Hierarchical planning framework consisting of multiple layers.

Then we post-process these observation points with an existing Travelling Salesman Problem (TSP) solver to generate a meaningful paths and route the AUV from its initial location to visit all generated way-points with the minimized/shortest path length.

Lastly, the low-level motion planner takes into account the AUV's motion uncertainty caused by the ocean current disturbances. We map the discrete state space of MDP to continuous motion space and integrate the external disturbance into the stochastic transition model. The way-points generated from the information-driven planner are projected onto a fine grid map representing MDP's state space, and are used as local goal states for the purpose of local decision-making (navigation).

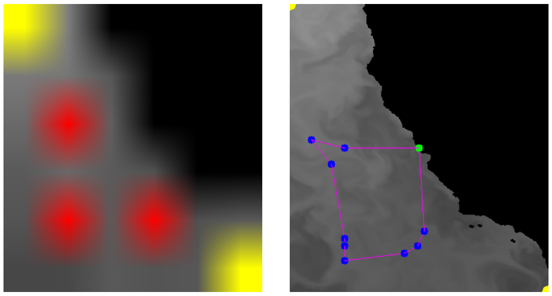
B. Hierarchical Information-Driven Planner

A series of sub-maps is constructed hierarchically, as illustrated in Fig. 1. The objective on each sub-map is to find a subset of sampling points of size n, P^*, which gives us the most information. It's equivalent to finding the maximum of the mutual information between the selected subset and the rest (unobserved part) of the sub-map, U. Thus the optimal P^* with maximal mutual information is

$$P^* = \underset{P \in \mathcal{X}}{\arg\max}\, I(Z_P; Z_U) \tag{1}$$

where $\mathcal{X}$ represents all possible combinatorial sets. $I(Z_P; Z_U)$ can be formulated with a recursive form and be solved using *dynamic programming*:

$$\begin{aligned} I(Z_P; Z_U) &= I(Z_{p_1}; Z_U) + \sum_{i=2}^{n} I(Z_{p_i}; Z_U | Z_{p_{1:i-1}}). \\ &\approx I(Z_{p_1}; Z_{W \setminus \{p_1\}}) \\ &\quad + \sum_{i=2}^{n} I(Z_{p_i}; Z_{W \setminus \{p_1, \ldots, p_i\}} | Z_{p_{1:i-1}}), \end{aligned} \tag{2}$$



(a) (b)

Fig. 2. Demonstration of hierarchical planning results with a total of 9 way-points. (a) The top layer of way-points (red) with priors in the corners (yellow). (b) A tour connecting the way-points (blue) generated from all sub-maps at the bottom layer. The green dot represents AUV's starting location.

where W denotes all the sampling points, and p_i denotes the sampling point in stage i.

With the whole set of observation points P_k^* in sub-map k. We recursively calculate finer observation points at each of their resided regions in P_k^* until the bottom layer is reached. The resultant points in the last layer are connected as a path/tour using any existing TSP solver based on their spatial descriptions. In this way, the traveling cost is minimized, and the information gain is also better than the other myopic greedy scheme.

C. Disturbance-Aware Motion Planner

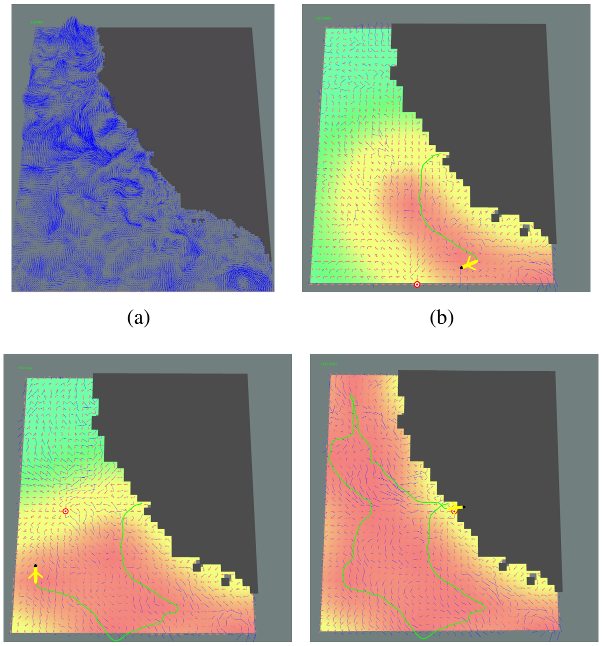
We design the low-level motion planner based on the decision-theoretic framework, and develop an adaptive disturbance-aware planning method built upon the Markov Decision Process (MDP) [3]. Specifically, the aforementioned high-level information-driven planner produces a series of informative path way-points. By setting the succeeding way-points as the short-horizon goal states, the low-level disturbance-aware motion planner generates policies for the local guidance.

III. Experimental Results

We validated our method in the scenario of ocean monitoring. The robot used in simulation is an underwater glider with a simplified kinematic model. The simulation environment was constructed as a two dimensional ocean surface and we tessellated the environment into grid maps. In our experiments, we use salinity and ocean current data observed in the Southern California Bight region. The raw data is obtained from ROMS [5].

Information-driven planning results from a two-layer framework is shown in Fig. 2. The red blobs are the observation points produced from the first layer, based on which the second layer generates a series of sampling points. By connecting with the AUV's starting location, a TSP tour is computed, as shown in Fig. 2(b).

Fig. 3(a) depicts the raw ocean current data obtained from ROMS. With the navigation way-points output from the hierarchical information-driven planner, the AUV follows local decisions represented by the MDP's optimal policy until it finishes the current batch of way-points. A resultant trajectory of the AUV is illustrated in Fig. 3(b)–3(d).



(a) (b)

(c) (d)

Fig. 3. (a) Raw ocean currents predicted by ROMS; (b)–(d) the AUV follows a series of way-points which cover the most uncertainty regions. The colormap depicts the variance of phenomenon prediction, where a warmer color represents a smaller variance. Blue lines are ocean currents and red arrows denote the MDP action policy.

The colormap in these figures denote the information-gain (informativeness), from which we can see that the proposed method produces informative path that explores and covers most of uncertain regions.

IV. Conclusions

In this paper, we presented an informative path planning method for long-term AUV ocean monitoring. The method takes into account both the spatio-temporal variations of ocean phenomena and the disturbances caused by the ocean currents. Specifically, the information-theoretic component employs a hierarchical structure and plans the most informative observation way-points; whereas the decision-theoretic component plans local motions by taking into account the non-stationary ocean current disturbances.

References

[1] A. Meliou, A. Krause, C. Guestrin, and J. M. Hellerstein. Nonmyopic informative path planning in spatio-temporal models. In *Proceedings of National Conference on Artificial Intelligence (AAAI)*, pages 602–607, 2007.

[2] R. Ouyang, K. H. Low, J. Chen, and P. Jaillet. Multi-robot active sensing of non-stationary gaussian process-based environmental phenomena. In *Proceedings of the 2014 International Conference on Autonomous Agents and Multi-agent Systems*, pages 573–580, 2014.

[3] M. L. Puterman. *Markov Decision Processes: Discrete Stochastic Dynamic Programming*. John Wiley & Sons, Inc., 1st edition, 1994.

[4] C. E. Rasmussen and C. K. I. Williams. *Gaussian Processes for Machine Learning (Adaptive Computation and Machine Learning)*. The MIT Press, 2005.

[5] A. F. Shchepetkin and J. C. McWilliams. The regional oceanic modeling system (ROMS): a split-explicit, free-surface, topography-following-coordinate oceanic model. *Ocean Modelling*, 9(4):347–404, 2005.