Statement of Thesis Research: Multi-Robot Sampling Strategies for Large-Scale Oceanographic Experiments

Jnaneshwar Das
Robotic Embedded Systems Lab
Department of Computer Science, University of Southern California
Los Angeles, California 90089
email: jnaneshd@usc.edu

My thesis research focuses on developing tools and techniques in the robotic sciences to study and understand large-scale dynamic coastal processes that are driven by global climate change. As a first step, my work targets Harmful Algal Blooms (HABs) which have significant societal and economic impact to coastal communities, yet are poorly understood ecologically because of undersampling.

Background

While my affiliation is to the Robotic Embedded Systems Lab at USC, I have worked with my advisor Prof. Gaurav Sukhatme to build up a collaboration with biologists and oceanographers both at USC and at the Monterey Bay Aquarium Research Institute (MBARI). Funding from the Center for Embedded Network Sensing (CENS), an NSF Science and Technology Center, allows me to work in this uniquely inter-disciplinary space where my primary interactions are with scientists in the pure sciences. My early work was in developing navigation and control algorithms for robotic boats used for study of HABs in marinas and lakes (de Menezes Pereira, Das, and Sukhatme 2008), which has had a direct effect on how water quality sensors are deployed and samples acquired. For my masters thesis, I designed and developed a prototype benthic robotic system deployed at the bottom of a body of water, enabling marine biologists to study the water column in a non-intrusive and energy-efficient manner (Das and Sukhatme 2009).

Recent and ongoing work

My research is situated in the problem domain of *Adaptive Sampling*. In the context of marine robotics, two important open problems are a) planning where to deploy robotic assets and b) once deployed, how observed data can be used to plan exploration strategies to maximize science return. Although this is an active area of interest with a significant contribution to environmental sampling (Krause, Singh, and Guestrin 2008; Zhang 2008; Rahimi et al. 2003), the problem of using multi-robot systems to observe large-scale dynamic phenomena observed in the ocean remains an open challenge. My early work at USC and MBARI has been on planning where to deploy robotic assets. This work uses remote sensing and ocean surface current measurement data to make short-term predictions of bloom trajectories, which in turn are used to plan surveys for Autonomous Underwater Vehicle (AUV) (Das et al. 2010b).

MBARI's AUVs run an AI-based onboard adaptive controller, the Teleo-Reactive EXecutive (**T-REX**) (McGann et al. 2008), that integrates automated planning and probabilistic state estimation within a hybrid executive. Initial experiments were carried out using a T-REX enabled AUV to sample within the context of an advecting patch of water. The patch of interest was tagged with a GPS-tracked drifter and the AUV surveyed within the Lagrangian frame of reference of the advecting patch (Das et al. 2010a). We are investigating a multi-criteria utility based technique to acquire discrete water samples using AUVs. Each function describes a desired property for the acquired sample and the total utility represents the 'goodness' of the sample. When above a desired threshold, the sampler is triggered and the sample acquired.

Onboard sampling strategies often need to be augmented by onshore capabilities in the marine domain. We are investigating how onshore and onboard autonomy can work in conjunction with humans in the loop, collaboratively enabling sampling driven problem-solving. This has led to the development of a prototype Oceanographic Decision Support System (ODSS) at MBARI as part of a multi-year mobile observatory called *Controlled, Agile, and Novel Observing Network* or CANON. In October 2010, the ODSS was used extensively to drive sampling for more than 20 autonomous robots in the Monterey Bay. Decision making was driven jointly by scientists, engineers and operational personnel from more than 15 institutions in the US.

Plans for future work

Having done preliminary work in robot deployment and onboard autonomy, the focus is now on extending and improving techniques developed at both USC and MBARI for adaptive water sample retrieval (McGann et al. 2008). Let $\left\{Z'(v) \mapsto [0,1] \subset \mathbb{R} : v \in \mathbb{R}^3\right\}$ be the normalized scalar field of interest (FOI) representing a biological feature (such as a HAB). The objective of the work is to gather water samples at the peaks of the FOI while satisfying constraints on the number of water samplers onboard the AUV, and the mission duration. Let $\left\{Z(v) \mapsto \mathbb{R}^n : v \in \mathbb{R}^3\right\}$ be a vector field of features that are correlated with the FOI $Z'(v)$. This is representative of typical oceanographic observation where proxy measurements are used to infer the extent of a desired biological feature of interest. During a mission, the robot takes measurements X_{v_i} from the multivariate proxy field $Z(v)$, at locations $v_i \in \mathbb{R}^3$,

$$X_{v_i} = Z(v_i) : X \in \mathbb{R}^n \tag{1}$$

An example of X_{v_i} could be a vector of proxy features like temperature, chlorophyll fluorescence or depth. Let $f(X)$ be a function that maps the multivariate proxy field to the scalar field representing the FOI

$$Z'(v) = f(Z(v)) : v \in \mathbb{R}^3 \tag{2}$$

Given, a measurement X_{v_i}, from Eqns 1 and 2, the corresponding estimate of the FOI at v_i is,

$$Y_{v_i} = f(X_{v_i}) \tag{3}$$

In (Fox et al. 2007), multi-dimensional input measurement vectors (e.g. chlorophyll fluorescence, turbidity, depth) were used to estimate Y_{v_i}, the probability of the observed sample being a biological feature of interest. The mapping from the proxy measurements to the feature of interest was learned from a training dataset containing features labeled as being within the FOI or outside by a cognizant scientist. This can be represented as follows: Let, T be a training dataset consisting of binary labeled data, where $T_i =< X_i, L_i >$, where $L_i = 1$ if the feature is of biological interest and $L_i = 0$ otherwise. From the training dataset, the mapping in Eqn. 3 is learned using Self-Organizing Map (SOM) clustering and a Hidden Markov Model (HMM).

The work can be improved in two ways. First, by building a spatial model of the FOI $Z'(v)$ that allows its estimation at unobserved locations. Currently, the spatial relationships between samples is implicitly captured in the HMM formulation. We propose using a non-parametric regression technique such as Gaussian process regression to build a probabilistic spatial model using data from a pilot survey (or on-going survey). The learned spatial model can then be used to compute optimal sampling paths to maximum science return. Second, by allowing the labeled training set to have non-binary labels, an expert can better guide statistical learning of the mapping between proxy measurements and the FOI.

Where it may be expensive or infeasible to obtain data labeled by experts, we are exploring unsupervised learning techniques to guide adaptive sampling strategies. A significantly large dataset gathered from a 2005 field experiment with multiple AUVs over a period of three weeks is being analyzed to observe the structure of its multi-dimensional input measurement space. If a trend is observed in the unlabeled data, in subsequent missions sampling can be biased towards measurements that deviate from the observed trend (control sample), or conforms to an existing norm (for reinforcement). We plan on utilizing techniques such as cluster-adaptive active learning (Dasgupta and Hsu 2008) from the machine learning literature, where the structure of observed data is used to guide sequential sampling.

Conclusion

The thesis research described preliminary work on deployment strategies for robotic assets, and ongoing work on on-board autonomy for AUVs. It has a direct impact on operational oceanography where it is necessary to close the gap between robot deployment constraints and the sampling needs for the coastal ocean. The techniques being developed are however applicable to other domains that require observation of dynamic phenomena with large spatio-temporal extent, e.g terrestrial environmental monitoring.

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