The University of British Columbia: Mechanical Engineering

Drone Based Water Monitoring for Optimal Information Gain

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Introduction

Waterborne environmental disasters are costly and becoming increasingly common. We are focusing on two in particular, flooding and oil spills. Climate change is making flood events, already the most damaging natural disaster in Canada, more common and more extreme. These floods bring water far inland, distributing salt and other contaminants.

Oil spills risk major damage to coastlines, coastal economies, and coastal ecosystems. Modelling has shown a major spill in the Salish Sea would coat a majority of the coastline without proper spill response.

Responses to these disasters would benefit from *in situ* water quality monitoring.

Environmental Disasters

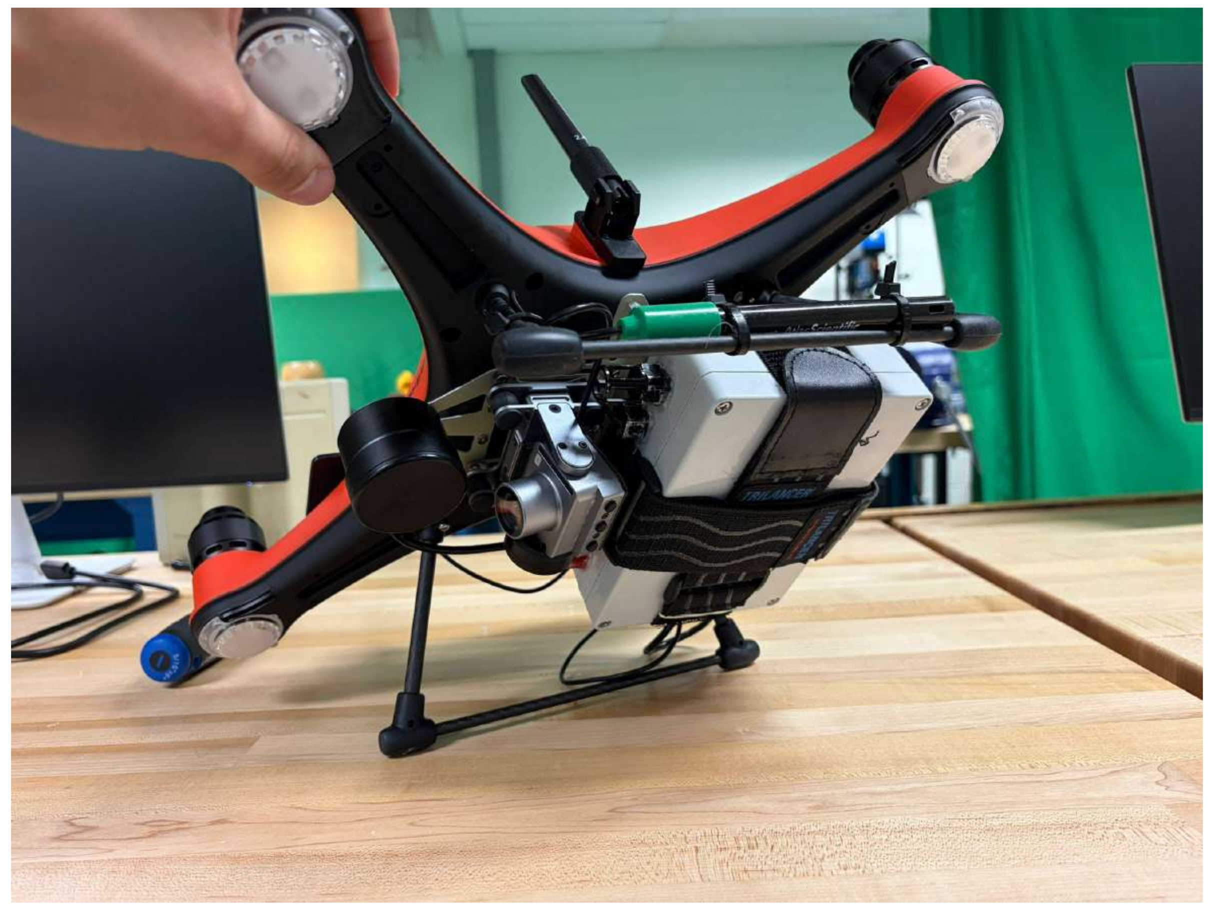
Water-based natural disasters that require monitoring include flooding (top, source CBC) and oil spills (bottom, source NOAA)

Current Hardware

We currently use a SwellPro Fisherman FD3 water landing quad-copter drone as the chassis of our system. We designed a base system that handles data transmission, and a modular system for sensors.

Equipment Setup

SwellPro Fisherman FD3 Drone with custom attachments. Shown with sensors for visual light (a camera), water depth, temperature, and conductivity (salinity).



Communications

The base system handles communication to and from the drone. This system:

- stores data locally;
- controls sensors;
- transmits real-time data to the cloud; and
- displays data on a user dashboard

Our system is not integrated with the drone controller, as we want the system to be agnostic to the chassis. The system can be attached to different types of drone (aquatic or aerial) with assorted sensors for varied sensing modalities.

Information collection

Collecting data points in a pattern without feedback from that data will not be optimal. We aim to improve data sampling efficiency by developing a framework for maximizing the information gathered within a given number of samples.

We use Bayesian experimental design, maintaining a belief state of the parameterized probability of an underlying field. We then treat the process of selecting sampling locations as experimental design while maximizing the expected information gain. We can loop between creating a sampling plan and updating the belief to approach an optimal sampling pattern

Optimal Problem Equations

$$\min_{u} C(z_K, z_0) + \sum_{k=1}^{K} ||u_k||^2$$

$$\begin{aligned}
s.t.\ z_{k+1} &= g(z_k, \hat{y}_k, x_k) & z_k &= (\theta_k, \Sigma_k)\\
\hat{y}_k &= \hat{h}_\theta(x_k) & \theta_k &\in \mathbb{R}^m\\
x_{k+1} &= f(x_{k+1}, u_k) & \Sigma_k &\in \mathbb{R}^{m\times m}\\
x_k &\in X & \beta &\in \mathbb{R}^+\\
u_k &\in U
\end{aligned}$$

$$\begin{aligned}
C(z_k, z_{k-1}) &= -D_{KL}(z_k || z_{k-1})\\
f(x_k, u_k) &= x_k + u_x\\
\hat{h}_\theta(x_k) &= \theta_k^T \phi(x_k)\\
\phi(x_k) &= (\phi_1(x_k) \cdots \phi_m(x_k))^T
\end{aligned}$$

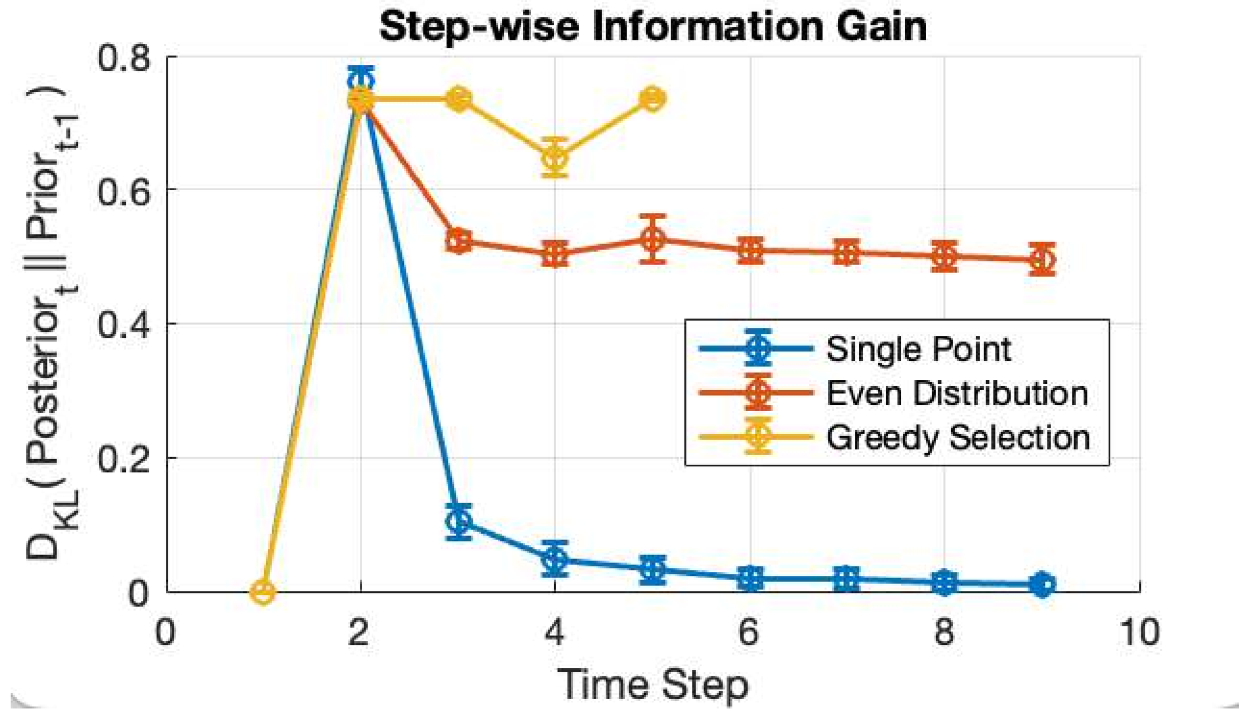
$$g(z_k, \hat{y}_k, x_k):$$

$$\begin{aligned}
\Sigma_{k+1} &= [\Sigma_k^{-1} + \beta\Phi^T(x_k)\Phi(x_k)]^{-1}\\
\theta_{k+1} &= \Sigma_{k+1}(\Sigma_k\theta_k + \beta\Phi(x_k)^T\hat{y})
\end{aligned}$$

$$\Phi(x) = \begin{pmatrix} \phi_0(x_1) & \phi_1(x_1) & \cdots & \phi_{M-1}(x_1)\\ \phi_0(x_2) & \phi_1(x_2) & \cdots & \phi_{M-1}(x_2)\\ \cdots & \cdots & \ddots & \cdots\\ \phi_0(x_n) & \phi_1(x_n) & \cdots & \phi_{M-1}(x_n) \end{pmatrix}$$

Stepwise Information gain

The improvement in information gain can be seen between different sampling plans. A greedy (optimized only over the next step) outperforms even distribution sampling.



Next Steps

Our next step is to implement the optimized problem in simulation. We will then create a two-part route planner for the drone. The first part will consist of an ML model trained to approximating the "true" solution, the second part being an MPC controller that will enforce physical and safety constraints on the drone.

Acknowledgement

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