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Presentations

Title

Adaptive Sampling in Environmental Robotics

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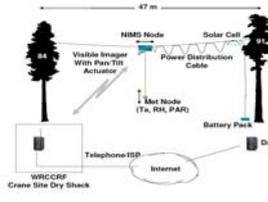
Adaptive Sampling in Environmental Robotics

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Exploiting Mobility for Environmental Science

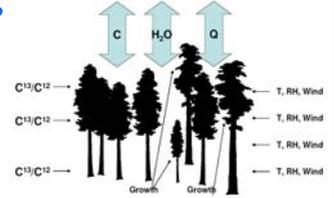
Motivation

- **Networked Informechanical Systems (NIMS)**
- Enables mobility for application science by
 - Extended visibility using motion
 - Sensing close to the phenomena
 - Interaction of mobile and static sensors
- We need mechanisms
 - Make NIMS an efficient tool for observing phenomena.
 - Enable scientists to create and verify a model of their observations.



Why is it Important?

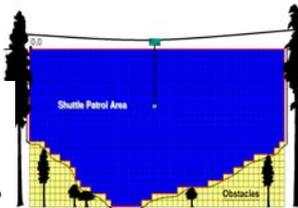
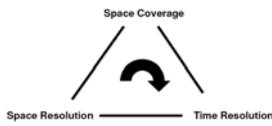
- Environmental Science
- Habitat monitoring
- Example
 - Aging in forests
 - CO₂ Respiration
 - Global warming at microclimate level
 - Comparison of different forests (ex. Oxygen generation)



Creating Dynamic Map of the Environment based on some sensing attribute

Goal

- There are constraints associated with locomotion and sampling.
- Maximize information about underlying phenomena within constraints of the system.
- Optimize the trade-off of Spatial resolution, temporal resolution and spatial coverage.
- Create a Map of the phenomena

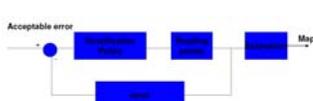


Sampling Policy

- Robot as a **Geostatistical Agent**
- Sampling has a cost
 - Time, Energy
- Limited sampling budget
 - Limited time to follow a dynamic phenomena
 - Limited energy
- Divide the environment into pixels.
 - Sample pixels to create a map (image) of the phenomena
- Sampling techniques
 - Uniform, random, stratified and nested stratified

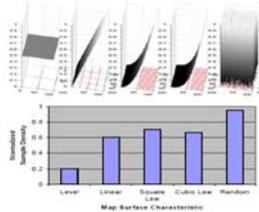
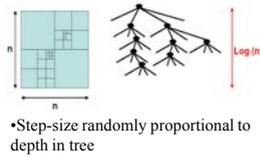
Experimental Deployment and Initial simulation results

Spatial Error and Adaptive Sampling

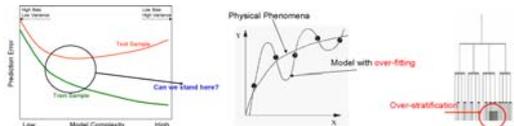


Divide and Conquer

- **Stratify** the current cell into four
- $\mu = \alpha * \text{cell size}$ (μ is mean of step size)
- **Collect data** in current cells (**Gaussian**)
- Calculate the **variance**
- **Iterate** until variance is below threshold



Bayesian Information Criterion



Adding model complexity may lead to **over-fitting** or **over-stratification**

A Regulatory Scheme

- Enabled by a cross validation
- **Information Criterion** techniques
 - Relying on **in-sample** data
 - Penalty for complexity

$$BIC(I) = \frac{n}{2} \text{Log}(RSS) + \frac{K_I}{2} \text{Log}(n)$$

credit for how good it fit

penalizing increasing model dimension

$$BIC_{parent} = \frac{n_{samples}}{2} \text{Log}(\hat{\delta}^2) + \frac{1}{2} \text{Log}(n_{samples})$$

$$BIC_{child} = \frac{n_{samples}}{2} \text{Log}(\hat{\delta}_{00}^2 + \hat{\delta}_{01}^2 + \hat{\delta}_{10}^2 + \hat{\delta}_{11}^2) + \frac{4}{2} \text{Log}(n_{samples})$$

Experimental Deployment



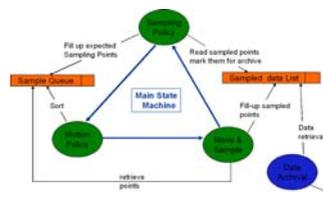
- At left is the map of Photosynthetic Active Radiation (PAR) and at right is the map of Relative Humidity at Boelter Hall, UCLA.



- Experimental Deployment at Wind River Canopy Crane Research Facility at Washington State. Compare the deployment scale with the canopy crane which is 87m tall in this panoramic view.



Implementation



- Optimization of mutual uncertainty of time & Space
- Incorporation of measurement costs.
- Development of continuous map models replacing piecewise continuous models.
- Multi-robot mapping
- Multi-variable mapping
- Mobile and static sensor collaboration
- Application of path planning methods to reduce frame time and minimize spatiotemporal error.
- Mapping in full three dimensional space