Title
Challenges in Adaptive Path Sampling with Mobile Sensors

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Challenges in Adaptive Path Sampling with Mobile Sensors

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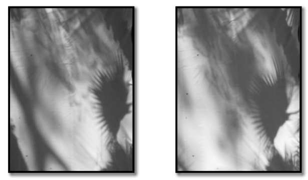
Introduction: Some applications naturally call for path samples rather than point samples

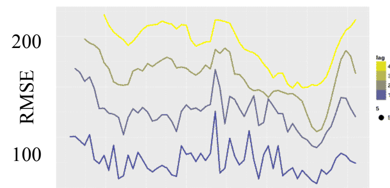
Solar Light Radiation and NIMS-3D

- **Solar light radiation can have high spatio-temporal variability**
  - Often, the strategy for estimating solar light radiation distributions is to find boundaries or other structures
- **NIMS-3D is mobile and capable of high sampling rates**
  - The PAR sensor uses little energy and can sample at about 10hz while the robot moves at about 14 cm/s.

Two Images Ten Minutes Apart



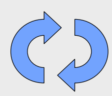
Pair-wise Image Differences Over Time



Problem Description: Algorithms originally developed for point samples rarely scale well

Adaptive sampling: a two-part problem

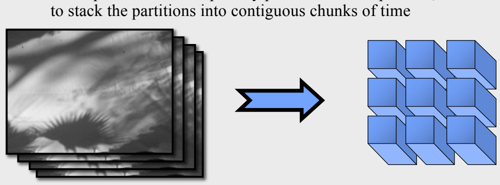
- **Part A: Where to sample next given the current model?**
  - One way to approximate paths is to bring to zero the sensor dwell time and energy requirements
  - The result is that a very small step is made to explicitly sample the next point, taking several minutes to traverse a few feet



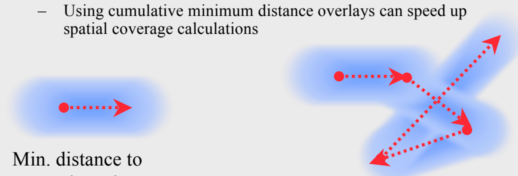
- **Part B: How to update the model based on current samples?**
  - Often, features calculated from the history of point samples are used to decide what to sample next
  - Standard interpolation algorithms for random fields, such as k-NN, bilinear interpolation, and kriging often result in large running times and huge memory requirements

Some techniques to help speed things up

- **Faster simulations: Spatio-temporal partitioning of the sample data**
  - In simulation and emulation, data samples from the environment are usually drawn from a time-series of images
  - An improvement is to spatially partition the sample data, and then to stack the partitions into contiguous chunks of time



- **Quickly update minimum distances between sampled points and all other points**
  - Many algorithms trade off spatial coverage and feature coverage
  - Using cumulative minimum distance overlays can speed up spatial coverage calculations

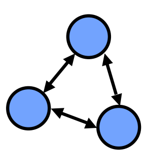


Min. distance to a sample path segment

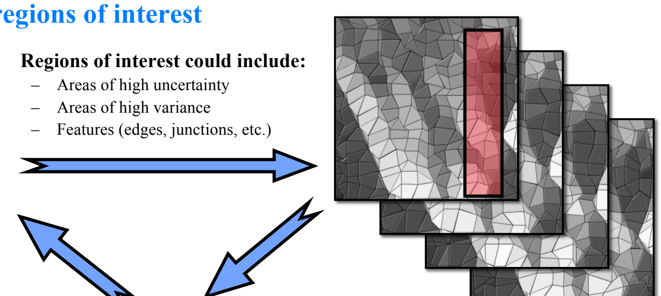
Cumulative overlay of min. distances

Proposed Solution: Bayesian regression with colored triangulation models

Part A: Sample the model to identify regions of interest

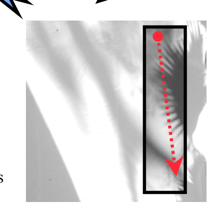


- **Regions of interest could include:**
  - Areas of high uncertainty
  - Areas of high variance
  - Features (edges, junctions, etc.)



Part C: Update model parameters

- **Parameters could include:**
  - Mean number of triangles
  - Distinct colored regions
  - Number and spacing of colors



Part B: Sample the environment

- **Sampling criteria could include:**
  - Favoring nearby areas
  - Maintaining spatial coverage

Advantages of this approach

- **Promotes paths to first-class citizens**
  - Represent samples as vertices and edges in free space instead of pixels in a matrix
- **Captures structuring elements in the data**
  - Intermediate pattern analysis: edges, junctions, and uniform regions
- **Easy to consider things beyond just interpolating the field**
  - Percentage of field in shadow
  - Distribution of sun fleck sizes
  - Distribution of sun fleck life-times

Challenges to this approach

- **Unclear what the right model is**
  - Entirely different triangulation models may be needed for different phenomena
- **Design and implementation of the sampler is tricky**
  - A fair amount of math is required to prove correctness of the sampler
  - Sampler must be efficient to minimize autocovariance times