Title

Adaptive Sampling by Using Mobile Robots and a Sensor Network

Authors

Zhang, Bin
Dhariwal, Amit
de Menezes Pereira, Arvind Antonio
et al.

Publication Date

2007-10-10

Adaptive Sampling Using Mobile Robots and a Sensor Network

Bin Zhang, Amit Dhariwal, Arvind Pereira, Jnaneshwar Das, Carl Oberg, Beth Stauffer, Lindsay Darjany, Xuemei Bai, David A. Caron, and Gaurav S. Sukhatme

Computer Science Dept. and Biological Science Dept., University of Southern California - Robotics.usc.edu/~namos

Introduction: Scalar Field Estimation

Static sensor nodes and mobile robots

- Advantages of static sensor nodes
  - Longer battery life
  - Higher temporal resolution
- Advantages of mobile robots
  - Higher spatial resolution
  - Ability to change the distribution of the readings

Main idea: Exploit advantages of both

- Static sensors
  - Uniformly deployed across the sensing field
  - Initial estimate generated from the sensor readings
- Mobile robots
  - Additional readings taken in critical locations
  - Estimate refined by using both initial and additional readings

Problem Description: Coordination between static sensor nodes and mobile robots

Problem Statement

- Given
  - A set of static sensor nodes uniformly distributed
  - A set of mobile robots
- Goal
  - Coordinate the motion of the mobile robots so that error associated with the reconstruction of the underlying scalar field is minimized

Assumptions

- Same sensors on mobile robots and static sensors
- Limited energy available to mobile robots
- No change in the scalar field during the data collecting tour
- Local Linear Regression used for estimation
- Centralized processing
- Accurate localization

Proposed Solution: Combining optimal experimental design and path planning

Definition of gain

- The Integrated Mean Square Error (IMSE) associated with Local Linear Regression can be estimated as follows:

$$\mathrm{IMSE}(X) \propto \int \left(\frac{tr^2\{\mathrm{H}_m(\mathbf{x})\}}{n^2 \hat{f}^2(\mathbf{x})} \right)^{\frac{2}{d+4}} d\mathbf{x}$$

  - $H_m(\mathbf{x})$ is the Hessian matrix, $\hat{f}(\mathbf{x})$ is the estimated local reading density and $X = \{x_0, x_1, \cdots, x_n\}$

- The gain associated with each location x is defined as the decrease of the IMSE if more sensor readings taken at x

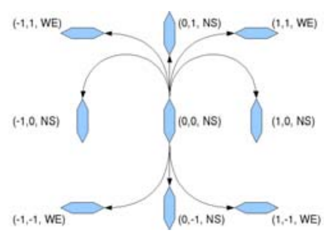
$$G(\mathbf{x}) = \mathrm{IMSE}(X_0) - \mathrm{IMSE}(X_0 \cup \{\mathbf{x}\})$$

Path planning for single mobile robot

- Approximate Breadth First Search: Maximizing gain collected with limited initial energy
- K-path: Minimizing the energy consumption while collecting given amount of gain
  - Based on the primal-dual schema
  - Approximation factor 2+δ for certain gain

Energy consumption model

- Based on a NAMOS boat
- The boat is assumed to have minimum turning radius
- Energy consumption is proportional to the distance traveled



Path planning for multiple mobile robots

- Assumptions: All robots have the same initial energy and share the same energy consumption model
- Generate graph representing state transition for single robot
- Partition graph into sub graphs with equal gain
- Assign one mobile robot to each sub graph and apply the path planning for single mobile robots