Decentralised Coordination of Mobile Sensors for Monitoring Dynamic Environments

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ATSN 2008
An online \textit{coordination mechanism} for a \textit{team} of autonomous \textit{mobile sensors} monitoring \textit{environmental phenomena}, e.g.

- Temperature
- Humidity
- Gas concentration
- Radiation
Outline

1 Motivation

2 Challenge

3 The Algorithm
   - Challenge 1: Information Processing
   - Challenge 2: Information Value
   - Challenge 3: Control

4 Demo & Evaluation

5 Conclusion & Future Work
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Motivation

Improve situational awareness in dynamic scenarios

- Disaster Response
- Military Surveillance
- Agriculture
Requirements

- Coordination of multiple sensors
- Online learning of environmental properties
- Decentralised action planning
- Recover both spatial and spatial correlations
Related Work

- Fixed sensor deployment
  - Offline, centralised
  - Spatial correlations only
- Mobile robotics
  - Pre-planning, centralised, single robot
  - Emphasis on localisation, mapping, tracking
Our Contribution

- Coordination Mechanism of Mobile Sensors
  - Online path planning
  - Online learning
  - Decentralised
  - Spatial and temporal correlations
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5. Conclusion & Future Work

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Central Challenge

How to move multiple mobile sensors to recover and predict the state of the phenomenon?

Three central questions:
1. How to *model* the phenomenon?
2. How to *value* individual samples?
3. How to *coordinate* to maximise value?
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Example Environment
Example Phenomenon
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Overview of the Algorithm

1. Take Measurements, Communicate and Process Information
2. Value of Information
3. Information-Based Control
Properties

- Online
- Decentralised
- Multi-Sensor
- Model Based
Information Processing

- Gaussian Process (GP): Bayesian regression over functions
  - Predict missing values (interpolate)
  - Predict future values (extrapolate)
GP Example
GP Example
GP Example
GP Example
GP Example
GP Example
Gaussian Process

- Covariance Function (CF) determines high level properties of process
  - Periodicity
  - Smoothness
  - Rate of change
  - Noise levels of environment and sensors
- *Hyperparameters* determine the strength of these properties
Hyperparameters: Long lengthscale

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Hyperparameters: Short lengthscale
Hyperparameters: Long timescale
Hyperparameters: Short timescale
Learn Hyperparameters

- Bayesian approach: marginalise out hyperparameters
- Bayesian Monte-Carlo: efficient numerical quadrature
Challenge 2: Valuing Information

- Intuition: obtain observations that minimise uncertainty
- Mathematical formalisation of uncertainty: Entropy
  \[ H(X) = - \int p(x) \log(p(x)) dx \]
- Closed form formula exists for Gaussian process
Valuing Information

How to minimise entropy (and thus uncertainty) in the environment?

1. Move sensors to positions with high entropy: maximise Entropy

2. Move sensors to positions at which their presence reduces uncertainty in the rest of the environment the most: maximise Mutual Information ($I$):

   $$ I(X; Y) = H(X) - H(X|Y) $$
Valuing Information

1. Maximise Entropy
   - Simple
   - Fixed sensors tend to be placed at the edges of the environment

2. Maximise Mutual Information
   - Computationally expensive
   - Fixed sensors tend to be placed more centrally (Guestrin 2005)
Valuing Information

![Diagram showing valuing information with different symbols and numbers on a grid.]

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Decentralised Coordination of Mobile Sensors
Different experimental results for mobile sensors:

No significant difference in performance between Mutual Information and Entropy.
Challenge 3: Information-Based Control

**Goal**
Minimise Entropy in the environment

**Simple Decision Rule**
Move in the direction of steepest Entropy gradient

**Resulting Behaviour**
Myopic Entropy maximisation
Challenge 3: Information-Based Control
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Emergent Properties

- “Chase out” uncertainty
- Implicit coordination & task allocation
Demo
Empirical Results

Simulated six policies using a real dataset from Intel Berkeley Labs

- **DCMC** Decentralised Coordination of Mobile Sensors (Our algorithm)
- **Random** Sensors that move randomly
- **A Priori** Sensors that know the hyperparameters in advance
- **Jump** Sensors that can “jump” to any desired location and know the hyperparameters
- **Fixed H** Fixed sensors that are deployed using the entropy criterion
- **Fixed MI** Fixed sensors that are deployed using the MI criterion
Empirical Results

Key metric: Root Mean Squared Error (RMSE) averaged over time

$$RMSE = \frac{\sum_{v \in V} (Predicted_v - Actual_v)^2}{|V|}$$

where:

- $V$: set of important locations in the environment
- $Predicted_v$: Predicted value at location $v$
- $Actual_v$: Actual value at location $v$
Empirical Results

![Graph showing average RMSE for different scenarios.]

1. DCMC
2. Random
3. A Priori
4. Jump
5. Fixed H
6. Fixed MI
Conclusion

- Coordination Mechanism for Mobile Sensors in dynamic environments
  - Modeling: Gaussian processes
  - Information Valuing: Entropy
  - Control: Myopic value maximisation
- Implicit coordination through observation sharing
- Interesting emergent properties
Future Work

- Towards more realistic environments
- Explicit cooperation
- Reason about paths