Spatiotemporal Aquatic Field Reconstruction Using Robotic Sensor Swarm

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Outline

• Motivation

• Rendezvous-based swarm scheme
  – Control-theoretic connectivity maintenance
  – Information-theoretic swarm center selection

• Performance evaluation

• Conclusion
Aquatic Field Reconstruction

- Guidance for future preventive actions
- Evolution of aquatic processes
  - Large area
  - Unpredictable spatiotemporal dynamics

Harmful Algal Blooms (HABs) in WI, 1999 (Photo Credit: Space Sci and Egr Ctr at UW-Madison and WisconsinView)

Chemicals/Waste Water pollution in UK, 2009 (Photo Credit: Reuters)

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Traditional Approaches

- Manual sampling
  - Labor intensive, coarse spatiotemporal granularity
- Fixed buoyed sensor
  - Limited spatial coverage, poor adaptability
- Mobile sensing via AUVs and sea gliders
  - Expensive (>50k), bulky, heavy

Manual sampling (left), fixed buoyed sensor (middle); AUV (right)

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Autonomous Robotic Fish

- On-board sensing, control, and wireless communication
- Low manufacturing cost: ~$200-$500
- Limited energy supply, computation power
- Our methodology: tightly couple w/ aquatic process modeling, sensing (cyber), and motion control (physical)

A prototype of robotic fish (left), and its internal components (right)
Smart Microsystems Lab, MSU

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Mobility Improves Reconstruction Accuracy
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- Objectives
  - Find informative sampling positions
  - Reduce motion control overhead
Mobility Improves Reconstruction Accuracy

- Objectives
  - Find informative sampling positions
  - Reduce motion control overhead
  - Maintain robotic sensors connectivity
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Rendezvous-based Swarm Scheme

1) Sampling
2) Estimate connectivity
3) Decide swarm center

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Rendezvous-based Swarm Scheme

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4) Move

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Rendezvous-based Swarm Scheme

1) Sampling
2) Estimate connectivity
3) Decide swarm center
4) Move
5) Reconstruct

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Modeling Swarm Connectivity

- **Swarm connectivity**
  \[
  \overline{PRR}(R) \approx (1 - c) + c \times \text{erf}(c_1 \log R + c_2)
  \]
  - Avg of PRRs of each link btw the swarm head & a sensor
  - Trained model

- **Disturbances**
  - Dynamics of wireless link quality
  - Swarm topology with random sensor positions
  - PRR estimations based on # of (re-)transmissions

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Modeling Swarm Connectivity

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Control-theoretic Connectivity Maintenance

R1

e.g. PRR=0.54

desired
PRR 0.90

PRR = 0.54 < 0.90
Control-theoretic Connectivity Maintenance

e.g. PRR=0.54

\[ \text{desired} \ PRR \ 0.90 \]

\[ \text{PRR} = 0.54 < 0.90 \]

swarm radius ↓

\[ \text{e.g. PRR}=0.95 \]
Control-theoretic Connectivity Maintenance

- Discrete-time feedback control formulation

\[ \delta \rightarrow \text{Controller } G_c(z) \rightarrow \text{Swarm } G_p(z) \rightarrow \text{PRR} \]

**<reference>** desired swarm average PRR

**<control input>** swarm radius

**<controlled variable>** measured swarm average PRR

Disturbances

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Information-theoretic Swarm Center Selection

- Find the most informative sampling positions
  - Objective:
    \[ \Omega(S) = H[V \setminus S \mid H_C] - H[V \setminus S \mid H_C \cup S] \]
    - Heuristic: use swarm center to approx. whole swarm

- Mutual Information (MI)
  - Uncertainty drop at the whole unvisited area

- Posterior Entropy (PE)
  - Uncertainty drop at the swarm center

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Sensor Movement Scheduling

- Minimize the total movement distance
  - To prolong the lifetime of network
- Element mapping problem
  - Solved by Munkres assignment algorithm
  - Fish trajectories proved to be collision-free

Iteration $k - 1$

Iteration $k$
Evaluation Methodology

• Data traces
  – On-water ZigBee communication collected on Lake Lansing in wavy environments
  – Temperature map [Lake Fulmor, CA, 2006]

• Trace-driven simulation
  – Connectivity maintenance, reconstruction accuracy, etc.

• Implementation on TelosB platform
  – Sensor position assignment
  – PE-based scheduling
Connectivity Maintenance

Our approach quickly converges to the desired level

→ Our approach quickly converges to the desired level
Reconstruction Performance

→ Reconstruction accuracy quickly improves over time
Field Reconstruction

→ Reconstruction accuracy improves quickly
Overhead on TelosB Platform

Execution time on TelosB of PE-guided scheduling vs. # of measurements

→ with 30 measurements, the total execution time (including swarm center selection, position assignment, etc.) is about 1 minute for one sampling iteration
Conclusion

- Rendezvous-based swarm scheme
  - Reduce motion control overhead
  - Control-theoretic connectivity maintenance
  - Information-theoretic swarm center selection

- Evaluation in trace-driven simulation & real implementation