Q21: How do I efficiently collect marine environmental data?

Jie Wang, Xingjian Wang, Xuanchen Wu, Yanzuo Chen

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Valuable Ocean Data

- The oceans: 71% of the Earth's surface
  - Vast unexplored areas
- Ocean temperatures determine climate and wind patterns
  - Affects life on land
- Marine pollution severely damages ecosystems

Conventional Underwater Data Collection Methods

Technique	Limitations
Cable communication	• High cost • Limited distance
Satellite communication with sea surface buoys	• High cost • Low Rate
Multi-hop communication	• Deployment overhead • Constant maintenance

Efficient Underwater Sensor Network Data Collection Employing Unmanned Surface Vehicles

Jie Wang, Xingjian Wang, Xuanchen Wu, Yanzuo Chen

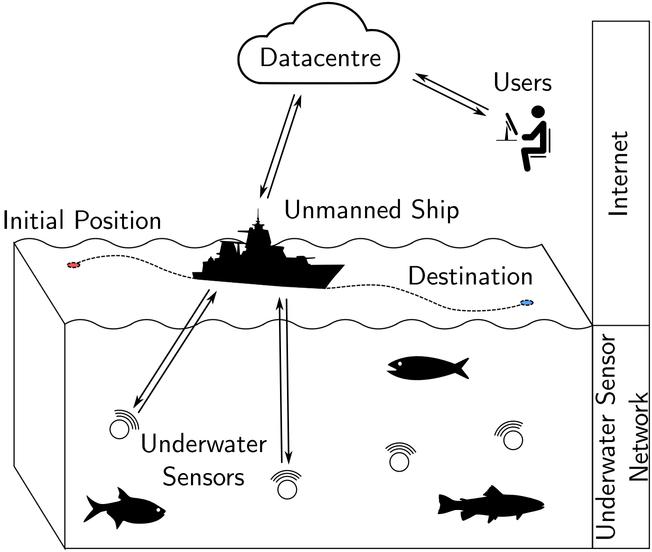
Network Coding Lab
The Chinese University of Hong Kong, Shenzhen

December 12, 2019

网络编码实验室
Network Coding Lab

Slides

Data Collection by Unmanned Ships



Constraints to Consider

- Communication channel loss increases exponentially!
- Limited battery and transmission power for Underwater Sensor Nodes (USNs)

As an Optimization Problem

Minimize the **maximum energy consumption** of all USNs by the joint design of...

- the **path** of the unmanned surface vehicle
- the **wake-up schedule** of the USNs

As an Optimization Problem

Challenges

- Non-convexity
- Large problem sizes (Number of USNs, transmission time slots)

Not efficiently solved by existing algorithms and off-the-shelf tools!

Solution

- Block-Coordinate Descent algorithm

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Underwater Acoustic Channel Model

Key assmptions[1]:

1. Gaussian Noise;
2. The k-th node transmits with power p_k;
3. Channel is separated into sub-channels, each with bandwidth Δf and frequency f_i.

Transmission Rate Approximation

The transmission rate for the k-th node over distance d is approximated as

$$C(d,k) = \sum_i \log_2 \left[1 + \frac{p_k/\Delta f}{N(f_i) \cdot A(d,f_i)} \right] \Delta f$$

where $A(d,f) \triangleq d^{\kappa}[\alpha(f)]^{d}$ denotes the attenuation factor; $N(f)$ denotes noise p.s.d.

1. Milica Stojanovic. 2007. On the relationship between capacity and distance in an underwater acoustic communication channel.

System Model

- An unmanned ship is to collect data from K USNs;
- Total time horizon is discretized into M time slots equally;
- Decision variable:

$\boldsymbol{q} := \{\boldsymbol{q}[m], 0 \le m \le M\}$	Path of unmanned ship
$\boldsymbol{x} := \{\boldsymbol{x}_k[m], 0 \le m \le M, 1 \le k \le K\}$	Wake-up schedule
$\boldsymbol{p} := \{p_k, 1 \le k \le K\}$	Transmission power of USNs

- Objective: minimize the maximum energy consumption for all USNs

$$\min_{\boldsymbol{p},\boldsymbol{q},\boldsymbol{x}} \max_{k} \sum_{m=0}^{M} x_k[m] p_k$$

System Constraints

- The path of the ship satisfies initial and final location constraints:

$$\boldsymbol{q}[0] = \boldsymbol{q}_0, \quad \boldsymbol{q}[M] = \boldsymbol{q}_f.$$

- The maximum speed constraints of the unmanned ship:

$$\|\boldsymbol{q}[m] - \boldsymbol{q}[m-1]\| \leq V_{\max}$$

- Wake-up mechanism:

$$\begin{cases} \sum_{k=1}^{K} x_k[m] \leq 1, & \forall m \\ x_k[m] \in \{0,1\}, & \forall m, \forall k \end{cases}$$

- Data Load Constraint:

$$\sum_{m=1}^{M} x_k[m] R(p_k, \boldsymbol{q}[m]) \geq b_k, \quad \forall k$$

Formulated Optimization Problem

The data collection scheme is formulated as the optimization problem[1]:

$$
\begin{aligned}
\min_{\boldsymbol{p},\boldsymbol{q},\boldsymbol{x},\theta} \quad & \theta \\
\text{s.t.} \quad & \textstyle\sum_{m=1}^{M} x_k[m] p_k \delta \le \theta, \quad \forall k = 1, \ldots, K \\
& \boldsymbol{q}[0] = \boldsymbol{q}_0, \quad \boldsymbol{q}[M] = \boldsymbol{q}_f \\
& \|\boldsymbol{q}[m] - \boldsymbol{q}[m-1]\| \le V_{\max} \\
& \textstyle\sum_{k=1}^{K} x_k[m] \le 1, \quad \forall m \\
& \textstyle\sum_{m=1}^{M} x_k[m] R(p_k, \boldsymbol{q}[m]) \ge b_k, \quad \forall k \\
& x_k[m] \in \{0, 1\}, \quad \forall m, \forall k
\end{aligned}
$$

1. Cheng Zhan, Yong Zeng, and Rui Zhang. 2018. Energy-efficient data collection in UAV enabled wireless sensor network

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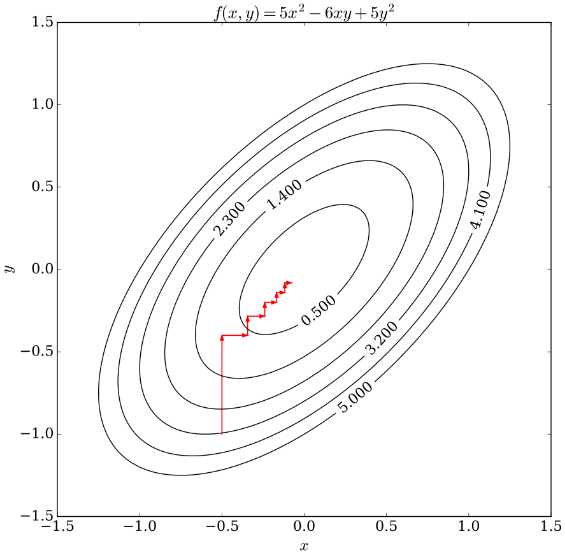
Objective function

$$
\begin{aligned}
\min_{\boldsymbol{p},\boldsymbol{q},\boldsymbol{x},\theta} \quad & \theta \\
\text{s.t.} \quad & \textstyle\sum_{m=1}^{M} x_k[m] p_k \delta \leq \theta, \quad \forall k = 1, \ldots, K \\
& \boldsymbol{q}[0] = \boldsymbol{q}_0, \quad \boldsymbol{q}[M] = \boldsymbol{q}_f \\
& \|\boldsymbol{q}[m] - \boldsymbol{q}[m-1]\| \leq V_{\max} \\
& \textstyle\sum_{k=1}^{K} x_k[m] \leq 1, \quad \forall m \\
& \textstyle\sum_{m=1}^{M} x_k[m] R(p_k, \boldsymbol{q}[m]) \geq b_k, \quad \forall k \\
& x_k[m] \in \{0, 1\}, \quad \forall m, \forall k
\end{aligned}
$$

- x : The sensor wake-up scheduling policy
- p : The sensor power policy
- q : The path planning policy of the ship

Coordinate Descent Algorithm



Iteration

Fixing $\boldsymbol{p}$ (sensor power policy), $\boldsymbol{q}$ (path planning), minimize over $\boldsymbol{x}$ (wake up schedule)

$$
\begin{aligned}
\min_{\boldsymbol{p},\boldsymbol{q},\boldsymbol{x},\theta} \quad & \theta \\
\text{s.t.} \quad & \textstyle\sum_{m=1}^{M} x_k[m] p_k \delta \le \theta, \quad \forall k \\
& \boldsymbol{q}[0] = \boldsymbol{q}_0, \quad \boldsymbol{q}[M] = \boldsymbol{q}_f \\
& \|\boldsymbol{q}[m] - \boldsymbol{q}[m-1]\| \le V_{\max} \\
& \textstyle\sum_{k=1}^{K} x_k[m] \le 1, \quad \forall m \\
& \textstyle\sum_{m=1}^{M} x_k[m] R(p_k, \boldsymbol{q}[m]) \ge b_k, \quad \forall k \\
& x_k[m] \in \{0, 1\}, \quad \forall m, \forall k
\end{aligned}
$$

Iteration

Fixing $\boldsymbol{p}$ (sensor power policy), $\boldsymbol{q}$ (path planning), minimize over $\boldsymbol{x}$ (wake up schedule)

$$
\begin{aligned}
\min_{\boldsymbol{x},\theta} \quad & \theta \\
\text{s.t.} \quad & \textstyle\sum_{m=1}^{M} x_k[m] p_k \delta \leq \theta, \quad \forall k \\
& \textstyle\sum_{k=1}^{K} x_k[m] \leq 1, \quad \forall m \\
& \textstyle\sum_{m=1}^{M} x_k[m] R(p_k, \boldsymbol{q}[m]) \geq b_k, \quad \forall k \\
& x_k[m] \in \{0, 1\}, \quad \forall m, \forall k
\end{aligned}
$$

Advantages

- Computational cost is usually less than other methods
- Sub-problems are usually easier to solve
- Ease of implementation

Trajectory Optimization

For fixed wake-up schedule $\boldsymbol{x}$ and transmission power policy $\boldsymbol{p}$,

$$\begin{aligned}
\max_{\boldsymbol{q},\eta} \quad & \eta \\
\text{s.t.} \quad & \|\boldsymbol{q}[m] - \boldsymbol{q}[m-1]\| \leq V_{\max}, \ \forall m = 1, \ldots, M \\
& \boldsymbol{q}[0] = \boldsymbol{q}_0, \boldsymbol{q}[M] = \boldsymbol{q}_f \\
& \frac{1}{b_k} \sum_{m=1}^{M} x_k[m] R(p_k, \boldsymbol{q}[m]) \geq \eta, \ \forall k = 1, \ldots, K
\end{aligned}$$

where $R(p_k, \boldsymbol{q}[m])$ is the *channel gain* at time slot m for sensor k:

$$R(p_k, \boldsymbol{q}[m]) \triangleq \sum_i \Delta f \cdot \log_2 \left(1 + \frac{A_{k,m}^{(i)}}{\|\boldsymbol{q}[m] - \boldsymbol{l}[k]\|^{\kappa} \cdot \alpha^{\|\boldsymbol{q}[m] - \boldsymbol{l}[k]\|}} \right)$$

Successive Convex Approximation

canonical form

$$\begin{aligned} \max_{\boldsymbol{q}} \quad & f_0(\boldsymbol{q}) \\ \text{s.t.} \quad & f_i(\boldsymbol{q}) \geq 0, \quad i = 1, \ldots, I \end{aligned}$$

Traditional method is by applying $f_i(\boldsymbol{q}) \geq f_{i,\text{lb}}^{(\ell)}(\boldsymbol{q}), \forall q$:

convex relaxation

$$\begin{aligned} \max_{\boldsymbol{q}} \quad & f_0(\boldsymbol{q}) \\ \text{s.t.} \quad & f_{i,\text{lb}}^{(\ell)}(\boldsymbol{q}) \geq 0, \quad i = 1, \ldots, I \end{aligned}$$

- Easy to solve the relaxation problem
- Solution is feasible to the nominal problem.

Standard SCA is not Applicable!

$$
\begin{aligned}
\max_{\boldsymbol{q},\eta} \quad & \eta \\
\text{s.t.} \quad & \|\boldsymbol{q}[m] - \boldsymbol{q}[m-1]\| \leq V_{\max}, \ \forall m = 1, \ldots, M \\
& \boldsymbol{q}[0] = \boldsymbol{q}_0, \boldsymbol{q}[M] = \boldsymbol{q}_f \\
& \tfrac{1}{b_k} \textstyle\sum_{m=1}^{M} x_k[m] R(p_k, \boldsymbol{q}[m]) \geq \eta, \ \forall k = 1, \ldots, K
\end{aligned}
$$

Global concave lower bound is not feasible to find

For the channel gain function

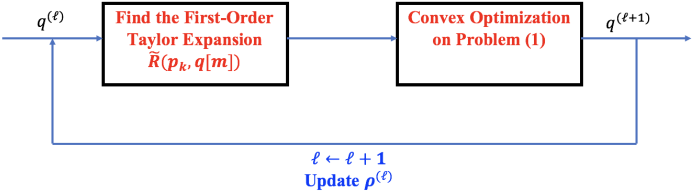
$$
R(p_k, \boldsymbol{q}[m]) \triangleq \sum_i \Delta f \cdot \log_2 \left(1 + \frac{A_{k,m}^{(i)}}{\|\boldsymbol{q}[m] - \boldsymbol{l}[k]\|^{\kappa} \cdot \alpha^{\|\boldsymbol{q}[m] - \boldsymbol{l}[k]\|}} \right),
$$

as long as $\alpha \neq 1$, the first-order taylor expansion is not its global concave lower bound.

SCA with Trust Region Heuristic

-

$$
\begin{aligned}
\max_{\boldsymbol{q},\eta} \quad & \eta \\
\text{s.t.} \quad & \|\boldsymbol{q}[m]-\boldsymbol{q}[m-1]\| \le V_{\max}, \ \forall m = 1,\ldots,M \\
& \boldsymbol{q}[0]=\boldsymbol{q}_0, \boldsymbol{q}[M]=\boldsymbol{q}_f \\
& \frac{1}{b_k}\sum_{m=1}^{M} x_k[m]\tilde{R}(p_k,\boldsymbol{q}[m]) \ge \eta, \ \forall k=1,\ldots,K \\
& \boldsymbol{q} \in \mathcal{T}^{(\ell)} \triangleq \{\boldsymbol{q} \mid \|\boldsymbol{q}-\boldsymbol{q}^{(\ell)}\| \le \rho^{(\ell)}\}
\end{aligned} \tag{1}
$$



Techniques Summarization

$$
\begin{aligned}
\min_{\boldsymbol{p},\boldsymbol{q},\boldsymbol{x}} \quad & \max_{k} \sum_{m=1}^{M} x_k[m] p_k \delta && \text{(12a)} \\
\text{s.t.} \quad & \|\boldsymbol{q}[m] - \boldsymbol{q}[m-1]\| \le V_{\max}, \ \forall m && \text{(12b)} \\
& \boldsymbol{q}[0] = \boldsymbol{q}_0, \boldsymbol{q}[M] = \boldsymbol{q}_f && \text{(12c)} \\
& \sum_{k=1}^{K} x_k[m] \le 1, \quad \forall m && \text{(12d)} \\
& \sum_{m=1}^{M} x_k[m] R(p_k, \boldsymbol{q}[m]) \ge b_k, \quad \forall k && \text{(12e)} \\
& x_k[m] \in \{0, 1\}, \quad \forall k, \forall m. && \text{(12f)}
\end{aligned}
$$

Convergence Comments

Our customized algorithm is guaranteed to converge.

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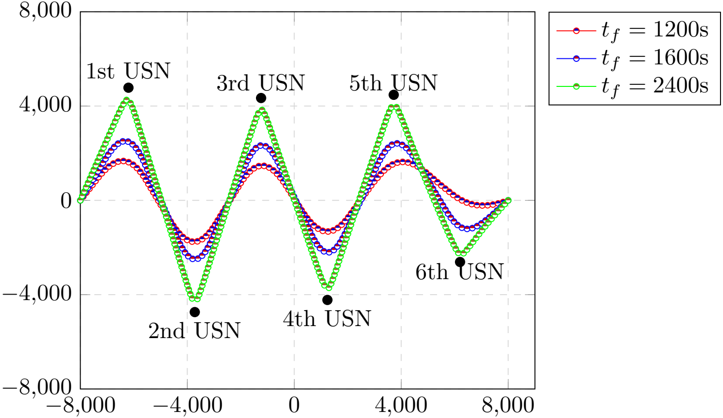
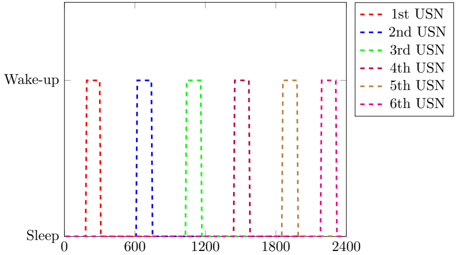
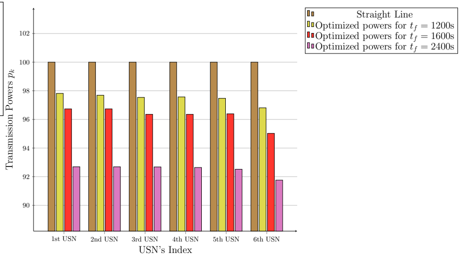
Numerical Simulation



Transmission Scheduling and Power Control





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Conclusion

- Data collection task by employing unmanned surface vechicles
- Jointly optimize the transmission scheduling, powers, and trajectory.
- Solving the non-convex optimization by:
    - block-coordinate descent
    - successive convex approximation with trust region heuristic
- Other useful techniques:
    - Approximate Dynamic Programming
    - Machine learning for online trajectory optimization

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