Q21: How do I efficiently collect marine environmental data?

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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

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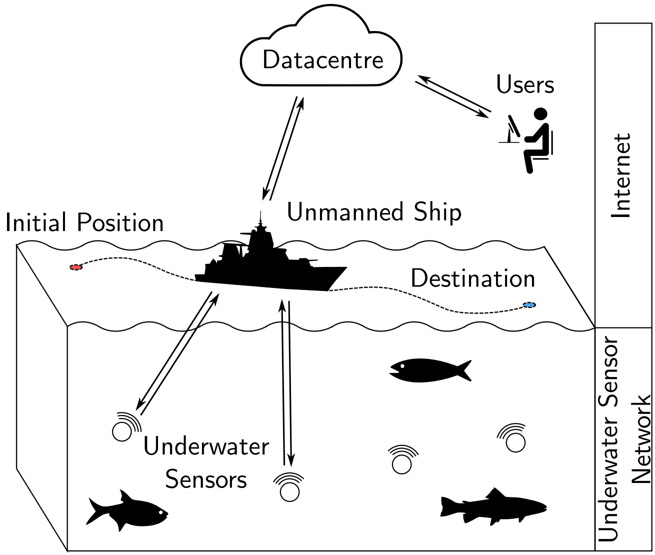
December 12, 2019

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:

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

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

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

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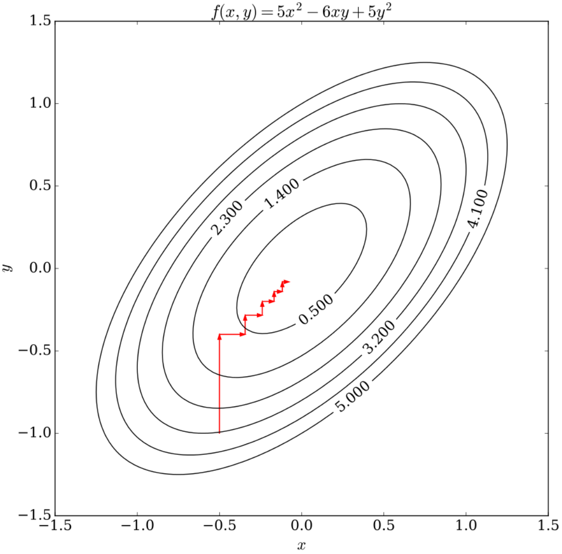
Objective function

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

- 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)

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

Iteration

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

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

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 $\boldsymbol{p}$,

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

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!

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

Global concave lower bound is not feasible to find

For the channel gain function

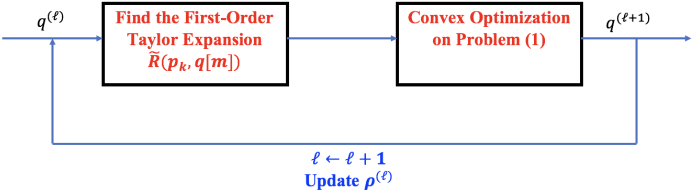
$$R(p_k,\boldsymbol{q}[m]) \triangleq \sum_i \Delta f \cdot \log_2\left(1+\frac{A_{k,m}^{(i)}}{\|\boldsymbol{q}[m]-\boldsymbol{l}[k]\|^{\kappa}\cdot\alpha^{\|\boldsymbol{q}[m]-\boldsymbol{l}[k]\|}}\right),$$

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

SCA with Trust Region Heuristic

-

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



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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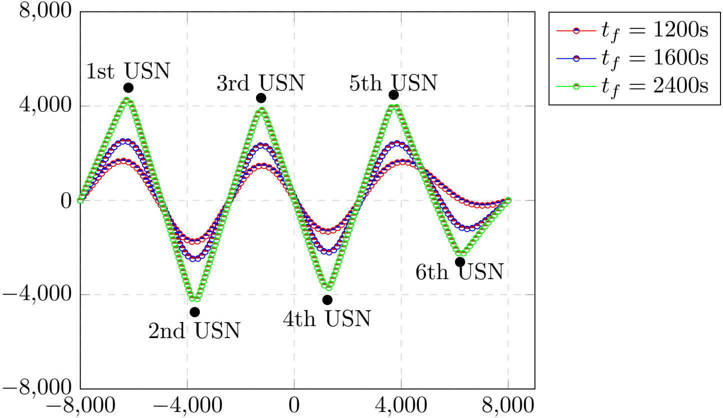
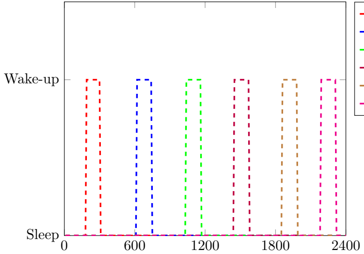
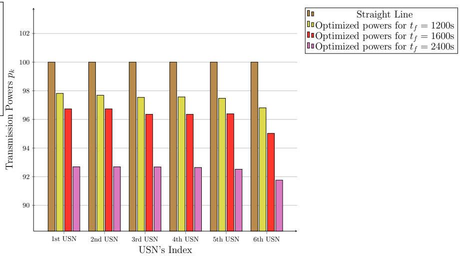
Numerical Simulation



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