Sensor Tasking and Control
Outline

- Task-Driven Sensing
- Roles of Sensor Nodes and Utilities
- Information-Based Sensor Tasking
- Joint Routing and Information Aggregation
- Summary
Introduction

- To efficiently and optimally utilize scarce resources (e.g., limited on-board battery and limited communication bandwidth) in a sensor network, sensor nodes must carefully tasked and controlled to carry out the required set of tasks.

- A utility-cost-based approach to distributed sensor network management is to address the balance between utility and resource costs.
  - Utility – the total utility of the data
  - Cost – power supply, communication bandwidth
Task-Driven Sensing

- A sensor may take on a particular role depending on the application task requirement and resource availability such as node power levels.

Example:
- Nodes, denoted by SR, may participate in both sensing and routing.
- Nodes, denoted by S, may perform sensing only and transmit their data to other nodes.
- Nodes, denoted by R, may decide to act only as routing nodes, especially if their energy reserved is limited.
- Nodes, denoted by I, may be in idle or sleep mode, to preserve energy.
Task-Driven Sensing

Base Station

Sensing and routing node

Idle node

Routing node

Sensing node

Sensors

Toxic Chemicals

T0+
Utility:

- We can define a utility function that assigns a scalar value, or utility, to each data reading of a sensing node.
- The maximum utility over a period of time is

$$\max \sum_{t} \sum_{i \in V_s(t)} U(i, t)$$

where i is sensor index and the set of nodes performing a sensing operation at time t as $V_s(t)$. 

**Generic Model of Utility and Cost**
Generic Model of Utility and Cost - Cont...

- Cost:
  - We can assign a cost to each sensor operation.
  - Example:
    - $C_s$: the cost of a sensing operation
    - $C_a$: the cost of data aggregation
    - $C_t$: the cost of data transmission
    - $C_r$: the cost of data reception
The constraint is defined as

$$\sum_{t} \sum_{V_s(t)} C_S + \sum_{t} \sum_{V_t(t)} (C_t + C_r) + \sum_{t} \sum_{V_a(t)} C_a \leq C_{total}$$

where the sets of nodes performing a sensing operation at time t as $V_s(t)$, aggregation nodes as $V_a(t)$, transmitting nodes as $V_t(t)$, and receiving nodes as $V_r(t)$. 
Utility vs. Cost

- More nodes are added, the benefit often becomes less and less significant.
Information-based sensor tasking is how to dynamically query sensors that information utility is maximized while minimizing communication and resource usage.

For a localization or tracking problem, a belief refers to the knowledge about the target state such as position and velocity.

This belief is represented as a probability distribution over the state space in the probabilistic framework.
Sensor Selection

Estimation uncertainty

Sensor a

Sensor b

It is good idea to select this sensor

Sensor selection based on information gain of individual sensor contributions
Sensor Selection – Cont..

- The estimation uncertainty can be effectively approximated by a Gaussian distribution, illustrated by uncertainty ellipsoids in the state space.

- Sensor b would provide better information than a because sensor b lies close to the longer axis of the uncertainty ellipsoid and its range constraint would intersect this longer axis transversely.
Scenario: Localizing a Stationary Source

Sensor a is farther from the leader node than the sensor b
Scenario: Localizing a Stationary Source – Cont..

- We assume these conditions:
  - All sensor nodes can communicate with each other.
  - Sensor a is farther from the leader node than the sensor b.

- There are four different criteria for choosing the next sensor:
  - A. Nearest Neighbor Data Diffusion
  - B. Mahalanobis distance
  - C. Maximum likelihood
  - D. Best Feasible Region

- These criteria will be postponed to the next section.
Localizing a stationary target

Sensor selection based on the nearest neighbor method. The estimation task here is to localize a stationary target labeled ‘*’. Square denote sensors. (a) Select the nearest sensor; (b) Incorporate the new measurement from the selected sensor.
Localizing a stationary target – Cont...

Sensor selection based on the Mahalanobis distance measure of information utility.
Algorithm

- A cluster leader selects optimal sensors to request data from using the information utility measures.
- Using the Mahalanobis distance measure, the cluster leader can determine which node can provide the most useful information while balancing the energy cost, without the need to have sensor data first.
- This algorithm presented here assume there is a single belief carrier node active at a time.
Information-Driven Sensor Querying (IDSQ)
Information-Driven Sensor Query

The measurement model for each sensor $i$ is

$$z_i = \frac{a}{\alpha} + \frac{x_i}{\|x - x_i\|^2} + w_i$$

For $i=1,\ldots,N$ where

- $a$ is the amplitude of the target uniformly distributed in the $[a_{\text{low}}, a_{\text{high}}]$, 
- $x$ is the unknown target position
- $x_i$ is the known sensor position
- $\alpha$ is the known attenuation coefficient, and
- $w_i$ is zero-mean Gaussian noise with variance $\sigma_i^2$. 

Step 1 - Initialization

The relevant characteristics of each sensor $i$ are

$$\lambda_i = \begin{bmatrix} x_i \\ \sigma_i^2 \end{bmatrix}$$

where $x_i$ is the position and $\sigma_i^2$ is the variance of the additive noise term.
Step 1 - Cont…

- The leader is chosen to be the one whose position $x_i$ is closest to the centroid of the sensor, that is,

$$\text{leader} = \arg_{j=1,...,N} \min \left| x_j - \frac{1}{N} \sum_{i=1}^{N} x_i \right|$$

- To determine the leader, all sensors communicate their characteristics $\lambda_i$ to each other
Step 2

- 2a Follower Nodes
  - When a following node $i$ is queried by the leader, it will transmit $z_i$ to the leader.

- 2b Initial Sensor Reading
  - The leader node becomes activated when the target is less than some given distance away from the leader node, assuming there is no other sound source present.

\[ z_{\text{leader}} > \gamma \]
Step 2 – Cont...

- The leader will then
  - store its amplitude value, \( \theta = z_{\text{leader}} \), which is its representation of the belief, and
  - keep track of which sensors’ measurements have been incorporated into the belief state,

\[ U = \{ \text{leader} \} \]
Step 3

- If the belief is good enough, based on some measure of goodness, the leader node is finished processing. Otherwise, it will continue with sensor selection.

- For the purposes of the experiments, we will continue to incorporate measurements until all sensors in the cluster have been incorporated.
Step 4 – Sensor Selection

A – Nearest Neighbor Data Diffusion

\[ \hat{j} = \arg_{j \in \{1, \ldots, N\} - U} \min \|x_{\text{leader}} - x_j\| \]

B – Mahalanobis distance

First, calculate the mean and covariance of the belief state

\[
\text{(mean)} \mu = \int x p(x | \theta) dx \\
\text{(covariance)} \sum = \int (x - \mu)(x - \mu)^T p(x | \theta) dx \\
\hat{j} = \arg_{j \in \{1, \ldots, N\} - U} \min (x_j - \mu)^T \sum^{-1} (x_j - \mu)
\]
Step 4 – Cont...

- After node $\hat{j}$ has been determined, a request transmitted to node $\hat{j}$, $Z_j$ received, the leader node will
  - update the representation of the belief state
    \[ \theta := \theta \cdot Z_{\hat{j}} \]
  - update the set of used sensors
    \[ U := U \cup \{\hat{j}\} \]
Experimental Results

Determine of the error covariance for selection criteria A and B.

Total communication distance vs. the number of sensors queried for selection criteria A and B.
Experimental Results – Cont...

Layout of seven randomly placed sensors (squares) with target in the middle (asterisk)

Percentage of runs where B performs better than A for seven randomly placed sensors
Experimental Results – Cont...

Percentage of runs where B performs better than C for seven randomly placed sensors

Percentage of runs where B performs better than D for seven randomly placed sensors
References


5.4 Joint Routing and Information Aggregation

- Our primary purpose is to collect and aggregate information.
- IDSQ just only provide us with a method to obtain max. incremental information gain.
- This section outlines some techniques to dynamically determine the optimal routing path.
5.4 Joint Routing and Information Aggregation – Cont…

Routing from a query proxy to the high activity region and back.
The ellipses represent iso-contours of an information field.

The goal of routing is to maximally aggregate information.

This differs from routing in communication networks where the destination is often known a priori to the sender.
Routing from a query proxy to an exit node.
5.4 Joint Routing and Information Aggregation – Cont…

- The routing has to maximize information gain along the path.
- A path toward the high information region may be more preferable than the shortest path.
Locally Optimal Search

- Individual sensors direct and guide the query by maximizing the objective function $J$.
- The local decisions can be based on 4 different criteria.

$$J(p(x|\{z_i\}_{i \in U} \cup \{z_j\}))$$

$$= \gamma \cdot \phi(p(x|\{z_i\}_{i \in U} \cup \{z_j\})) - (1 - \gamma) \cdot \psi(z_j)$$
1. each current sensor $k$ evaluate the objective function $J$, and pick the sensor $j$ that maximizes the objective function.

- $\zeta_j$ is the position of the node $j$.

$$^\wedge j = \arg \max_{j} (J(\zeta_j)), \forall j \neq k$$
2. Choose the next routing sensor in the direction of the gradient of the objective function, $\nabla J$.

$k$ is the position of the current routing node.

$$
\hat{j} = \arg \max_j \left( \frac{(\nabla J)^T \bullet (\zeta_j - \zeta_k)}{\|\nabla J\| \|\zeta_j - \zeta_k\|} \right)
$$
The optimum position corresponds to the location where the utility function $\zeta$ is maximized.

$$\zeta_o = \arg\min_{\zeta} [\nabla \phi = 0]$$

\[
J(p(x|\{z_i\}_{i \in U} \cup \{z_j\})) = \gamma \cdot \phi(p(x|\{z_i\}_{i \in U} \cup \{z_j\}) - (1 - \gamma) \cdot \psi(z_j)
\]
4. The optimal direction can be chosen, according to $\nabla J$ and the direct connection between the current sensor, $\zeta_k$, and the optimum position, $\zeta_0$.

- The parameter $\zeta$ can be chosen.

$$d = \beta \nabla J + (1 - \beta)(\zeta_0 - \zeta_k)$$
Simulation Experiments

\[
J(p(x|z_i)_{i \in U} \cup \{z_j\})) = \gamma \cdot \phi(p(x|z_i)_{i \in U} \cup \{z_j\}) - (1 - \gamma) \cdot \psi(z_j)
\]

- Following figure shows how variation of the trade-off parameter \( \gamma \) morphs the shape of the objective function.
- The value of the objective function is shown as a contour plot.
= 1

A question mark (?) depicts the position of the querying sensor.
The mark, T, depicts the target position.
$\theta = 0.2$
\[ \mathbb{I} = 0 \]
Simulation Experiments – Cont…

- As $\mu$ decreases from 1 to 0, the shape of the peak location moves from being at the target to the querying sensor.
- At the same time, the contours change from being elongated toward isotropic.
- The spatial position does not shift linearly with varying $\mu$. 
Simulation Experiments – Cont...
5.4.2 Multistep Information-Directed Routing

- The sensor selection is greedy, and may get stuck at local maxima.
- We use the inverse of Euclidean distance to measure the sensor’s information contribution.
A target is moving from X to Y.

The hand-offs continue back and forth between A and B.

The path never gets to nodes E, F, or G, as the target moves closer to Y.

The culprit is the “sensor hole”.

5.4.2 Multistep Information-Directed Routing – Cont…
Recently, local routing algorithms have been developed to traverse perimeters of sensor holes, but we don’t apply.

The routing destination is not known a priori in our problem.

Without knowledge about the destination, it is impossible to tell if the routing is stuck at a local optimum.
State-Dependency

- State-Dependent: how much new information a sensor can bring depends on what is already known.
- The information contribution of each sensor is state-dependent.
- State-dependent make standard shortest-path algorithms are no longer applicable.
State-Dependency – Cont...

(a)
State-Dependency – Cont...
State-Dependency – Cont...
State-Dependency – Cont...
State-Dependency – Cont...

- **MSE:**
  
  mean-squared error, the error in localization.

- **Information:**
  
  representing the effect how a sensor change the last belief.

<table>
<thead>
<tr>
<th></th>
<th>Information</th>
<th>MSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>step1, sensor A</td>
<td>0.67</td>
<td>11.15</td>
</tr>
<tr>
<td>step2, sensor B</td>
<td>1.33</td>
<td>10.02</td>
</tr>
<tr>
<td>step3, sensor C</td>
<td>1.01</td>
<td>9.00</td>
</tr>
<tr>
<td>step4, sensor D</td>
<td>0.07</td>
<td>8.54</td>
</tr>
</tbody>
</table>
State-Dependency – Cont...
5.4.3 Sensor Group Management

- In practical applications, the effect of a physical phenomena usually attenuates with distance.
- This gives rise to the idea of geographically based collaborative processing groups.
5.4.3 Sensor Group Management – Cont…
5.4.3 Sensor Group Management – Cont...

- Physical phenomena change over time.
- The collaborative groups also need to be dynamic.
- Else nodes may join the group, and current members may drop out.
- Geographically based group have to be achieved by a lightweight protocol.
5.4.3 Sensor Group Management – Cont…

- a lightweight protocol
  - This protocol needs to be powerful to handle complex situations.
  - This protocol needs to be robust to tolerate poor communication.
  - In addition, the propagation region should be restrained to only the relevant nodes.
Example: Information Migration in Tracking a Moving Target

- How can the information utility measures be applied to a tracking problem?
- Assume a leader node carries the current belief state.
- As the target moves through the field, a subset of sensors are activated to carry the belief state.
- The leader chooses a sensor in its neighborhood, and hands off the current belief to the chosen sensor (the new leader).
Example – Cont...

Estimate at t
Example – Cont...

Estimate at $t$

Estimate at $t+1$
Example (Con.)

Estimate at $t$

Estimate at $t+1$
Example – Cont…

Estimate at t

Estimate at t+1

Estimate at t+2

A → B
Example – Cont…

Estimate at t

Estimate at t+1

Estimate at t+2

A

B

C
Distributed Group Management

- A collaborative group—a set of sensor nodes responsible for the creation and maintenance of a target’s belief state.

- Following figure shows how the leader node maintains and migrates the collaborative processing group.
Distributed Group Management – Cont…

(a) After the leader is elected, it initializes a belief state as a uniform disk $R_{\text{detect}}$. 

![Diagram showing a belief state as a uniform disk $R_{\text{detect}}$ with a target at the center and some nodes distributed around it.](diagram.png)
Distributed Group Management – Cont…

- (b) The leader calculates a suppression region and informs all group members in the suppression region to stop detection.
Distributed Group Management – Cont...

- A new leader is selected using a sensor criterion.
- The current belief state is handed off to the new leader.
5.4.4 Case Study: Sensing Global Phenomena

- We have been primarily concerned with sensing point targets so far.
- In some situations, we might encounter the problem of sensing a global phenomenon.
- The primary challenge is to relate a local sensing action to the global property of the objects.
Case Study – Cont...

- To address this challenge, we use the primal-dual transformation into our analysis.

- Primal-dual transformation:
  mapping a line in the primal space into a point in the dual space, and vice versa.
Case Study – Cont…

- Primal-dual transformation:

In the image, a diagram illustrates the primal-dual transformation with equations: $y = \alpha \cdot x + \beta$ in the primal space and $\varphi = a \cdot \theta + b$ in the dual space. The points $(a, b)$ and $(-\alpha, \beta)$ are marked in the respective spaces.
Case Study – Cont…

primal space

\[ L: y = \alpha \cdot x + \beta \]
Case Study – Cont…

\[ p_4 : \varphi = a_4 \cdot \theta + b_4 \]
\[ p_3 : \varphi = a_3 \cdot \theta + b_3 \]
\[ p_2 : \varphi = a_2 \cdot \theta + b_2 \]

\[ l(-\alpha, \beta) \]
Case Study – Cont…

- The number of lines bounding a cell is 4 on the average.
- No matter how many sensors are present in the field, the number of active sensors is very small.
5.5 Summary

- We have developed a number of important ideas for allocation the sensing, processing, communication, and other application tasks.
Some key themes emerge from these discussions:

- Central to these ideas is the notion of information utility, and the associated costs of acquiring the information.
- The information utility measures can take on many different forms. However, inappropriate uses of information utility may consume intolerable amounts of resources and diminish the benefit.
5.5 Summary – Cont…

- We must rethink the role of routing:
  - Routing in a sensor network often does not just perform a pure information transport. It must be co-optimized with the information aggregation or dissemination.
  - A group of sensors collectively support a set of tasks. The challenge is to efficiently create, maintain, and migrate groups.
The End