POSE, POSE.3C and POSE.R Algorithms: Prediction-based Opportunistic Sensing for Energy-Efficiency and Resilience in Distributed Sensor Networks

Applications to Target Tracking Sensor Networks

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Publications below contain detailed updated material.
Intelligent Sensor Networks

Applications

Intelligence, Surveillance, and Reconnaissance

Example Applications:
- Border Security
- Battlefield Surveillance
- Anti-submarine Warfare


Smart Cities and Homes

Example Applications:
- Traffic Light/Traffic Control
- Intelligent Parking Systems
- Activity Monitoring


Environmental Monitoring

Example Applications:
- Habitat Monitoring
- Disaster Monitoring


Wireless Body Sensor Networks

Example Applications:
- Monitoring Personal Well being
- Activity Monitoring

Intelligent Sensor Networks
Challenges and Current Approaches

**Target Coverage**

**Energy Efficiency**
- Finite energy resources
- Replacement is difficult

**Resilience**
- Network density may be low or non-uniform
- Sensor nodes are fixed and can fail

**Network Control Architecture**

- **Centralized**
  - Sensor Selection to Minimize Estimation Error, Distance, Energy, etc.
  - Duty-cycle
  - Triggered Activation
  - Random Scheduling

- **Cluster-based**
  - Resilient target coverage for stationary networks does not exist
  - Density of target’s predicted location is not used for control

- **Distributed**
  - Active fault detection
  - Passive fault detection
  - Proactive fault recovery
  - Reactive fault recovery

**Scheduling Strategies**

- Sensor Selection to Minimize Estimation Error, Distance, Energy, etc.
- Duty-cycle
- Triggered Activation
- Random Scheduling

**Fault Tolerance**

- Active fault detection
- Passive fault detection
- Proactive fault recovery
- Reactive fault recovery

**Challenges**

- Finite energy resources
- Replacement is difficult
- Network density may be low or non-uniform
- Sensor nodes are fixed and can fail

**Research Gaps**

- Coverage Gaps
- Missed Detections
- Mission Suspension
- Energy Wastage
**Problem Formulation**

**Problem Statement**

**Objective:** Develop a network autonomy approach that utilizes distributed supervisors (Probabilistic Finite State Automaton) to probabilistically control multi-modal sensor nodes that meets the following requirements:

1. Extended network lifetime
2. Resilient target coverage
3. High tracking accuracy
4. Low missed detection rates

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**Theme 1: Prediction-based Opportunistic Sensing (POSE)**
- Distributed Supervisors for probabilistic control of Multi-modal sensor nodes
- Prediction-based Opportunistic Sensing for energy-efficient control

**Theme 2: POSE using Distributed Classification, Clustering and Control (POSE.3C)**
- Distributed Classification for opportunistic sensing of Targets Of Interest
- Distributed Clustering via efficient sensors selection
- Distributed Control

**Theme 3: POSE for Resilience (POSE.R)**
- Prediction-based Opportunistic Coverage
- Resilient target coverage via distributed learning and sensor range adjustment
- Enhanced distributed clustering

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**Energy Efficiency**
- Classification feedback
- Sensor selection

**Resilience**
- Resilient Target Coverage

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**Novel Contributions**
Problem Formulation

Multi-modal Sensor Node Description

Each Multi-modal Sensor Node, $s_i$, is equipped with:

1. Data Processing Unit (DPU)
   - Performs necessary calculations
   - Facilitates decision-making to enable or disable each device at time $k$

2. Transmitter (TX) / Receiver (RX)
   - Allows for data transmission between sensor nodes

3. Low Power Sensing (LPS) Device
   - Passive binary detectors that consume little energy, e.g., Passive Infrared (PIR) sensor
   - Allows for low power target detection, up to a distance $R_{s,LPS}$

4. High Power Sensing (HPS) Device
   - Allows for accurate measurement of the target up to a distance $R_{s,HPS}$
   - This could be a Camera, Laser, Radar, Sonar, or other sensing devices

Energy Model

Individual Sensor node energy consumption [1]:

$$E^{s_i}(k) = \sum_k \sum_j e_j^{s_i} \cdot \chi_j^{s_i}(k) \Delta T$$

- $e_j^{s_i}$: The rate of energy consumption per unit time of device $j \in \{DPU, LPS, HPS, TX, RX, Clock\}$
- $\chi_j^{s_i}(k) \in \{0,1\}$: Indicates whether the device is On or Off at time $k$
- $\Delta T$: The sampling interval

Network energy consumption:

$$E_{net}(k) = \sum_{i=1}^{n} E^{s_i}(k)$$

- $n$: Number of sensor nodes deployed

Problem Formulation

Target Description

Target Dynamics

Target Motion Model: Discrete White Noise Acceleration Model [1]

\[ x^T(k + 1) = f(x^T(k), k) + v(k) \]

- \( x^T(k) = [x, \dot{x}, y, \dot{y}, \phi]' \): Target, \( \tau \), state at time \( k \)
- \( f(\cdot, k) \): State transition matrix, and
- \( v(k) \): White noise acceleration sequence with \( E[v(k)] = 0 \) and \( E[v(k)v(k)'] = Q \).

Measurement Models

HPS Device Measurement Model:

\[ z(k) = (z_1(k), \ldots, z_m(k)) \]
\[ z_j(k) = h(x^T(k), k) + \omega(k) \]

- \( z(k) \): Set of measurements received
- \( z_j(k) \): Range and azimuth measurement of target or clutter
- \( m \): Number of measurements received
- \( h(\cdot, k) \): Measurement model, and
- \( \omega(k) \): Measurement noise w/ \( E[\omega(k)] = 0 \) and \( E[\omega(k)\omega(k)'] = R \).

LPS Device Measurement Model:

\[ z(k) \in \{0,1\} \]

LPS Device Detection Model [2]:

\[ p_{D,LPS}^{s_i}(k) = \begin{cases} \alpha & ||u^{s_i} - u^T(k)|| \leq R_r \\ e^{-\beta(||u^{s_i} - u^T(k)|| - R_r)} & R_r < ||u^{s_i} - u^T(k)|| \leq R_{s,LPS} \\ 0 & ||u^{s_i} - u^T(k)|| > R_{s,LPS} \end{cases} \]

- \( \alpha \) and \( \beta \): Model Design Parameters
- \( R_r \): LPS device reliable sensing range

Objective: Develop a network autonomy approach that utilizes distributed supervisors (Probabilistic Finite State Automaton) to probabilistically control multi-modal sensor nodes that meets the following requirements:

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Problem Statement

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- Enhanced distributed clustering

Target Coverage

Energy Efficiency

Resilience

Novel Contributions

- Classification feedback
- Sensor selection
- Resilient Target Coverage
POSE

Main Idea

Target Predicted LPS Detection Area

Target Predicted HPS Detection Area

Sensor Node

Legend
• $R_{s,LPS}$: LPS Sensing Range
• $R_{s,HPS}$: HPS Sensing Range

Legend
- Sleep State
- Low Power Sensing (LPS) State
- High Power Sensing (HPS) State

High Power Sensing (HPS) State

Low Power Sensing (LPS) State

Sleep State

Opportunistically turn-on high power sensing around target's predicted position in a distributed manner.
POSE

Distributed Supervisor: Probabilistic Finite State Automaton (PFSA)

Multi-Modal Sensor Node Control Diagram

- Consumes minimal energy
- Target detection while conserving energy
- Performs state estimation
- Alerts neighbors of target whereabouts

Distributed Supervisor Layer

High Power Sensing (HPS) Device (e.g. Laser)

Transmitter/Receiver/GPS

Data Processing Unit

Low Power Sensing (LPS) Device (e.g. PIR)

PIR: Passive Infrared Sensor

In the published POSE paper we used a 4-state PFSA for distributed control. Here we combined the Listening and LPS states together for compactness and simplicity.
### Objective
Minimize energy consumption by disabling all devices

### Description
- Designed to minimize energy consumption when a target is away from the sensor node
- All devices except a clock are disabled

### State Transition Probabilities

<table>
<thead>
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<th>State Transition Probabilities</th>
<th>Sleep</th>
<th>LPS</th>
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<tbody>
<tr>
<td>$p_{11}^{si}$</td>
<td>$p_{sleep}$</td>
<td>$p_{12}^{si}$</td>
<td>$1 - p_{sleep}$</td>
</tr>
</tbody>
</table>

Where $p_{sleep} \in [0,1]$ is a design parameter

LPS: Low Power Sensing
HPS: High Power Sensing
**Objective**
Detect the target while conserving energy

**Description**
- Only the DPU, LPS devices, and transmitter/receiver are enabled
- Desired to be enabled when a target is away
- Detection occurs using LPS devices or from information transmitted by neighbors.

**Legend:**
- $s_i$: Sensor node $i$
- $P_{D,LPS}^i$: Probability of detection of LPS Device
- $P_{HPS}^i(k)$: Probability that the target is located in HPS coverage area
- $p_{xy}^i(k)$: State transition probability from state $x$ to state $y$

**Figure:** Low Power Sensing State Algorithm
POSE
High Power Sensing (HPS) State Algorithm

Objective
Utilize HPS devices to estimate the target’s state and alert neighbors of target’s location

Description
• HPS devices, DPU, transmitter, and receiver are enabled
• Designed to only be enabled when a target is predicted to travel in the sensor nodes coverage area
• Provides a range and angle measurement of the target
• Performs state estimation
• Broadcasts target state estimates to neighbors
POSE
High Power Sensing (HPS) State Algorithm

Legend:
- \( s_i \): Sensor node \( i \)
- \( P_{HPS}^{s_i}(k) \): Probability that the target is located in HPS coverage area
- \( p_{xy}^{s_i}(k) \): State transition probability from state \( x \) to state \( y \)

Set of measurements \( z(k) \)

Is State Initialized

Previous target state estimates
\( \hat{x}_{s_i}^{s_i}(k-1|k-1), \hat{\Sigma}_{s_i}^{s_i}(k-1|k-1) \)

State Initialization

Association and State Estimation using JPDA

\( M \)-of-\( N \) Track Confirmation

\( \hat{x}_{s_i}^{s_i}(k|k), \hat{\Sigma}_{s_i}^{s_i}(k|k), \hat{W}_{s_i}^{s_i}(k|k) \)

Validated target state estimates and filter gain matrix

Information Received

Yes

Distributed Fusion

Joint Estimates of Targets

No

One-step Prediction

Compute \( P_{HPS}^{s_i}(k) \)

\[
\begin{align*}
p_{31}^{s_i}(k) &= 0 \\
p_{32}^{s_i}(k) &= 1 - P_{HPS}^{s_i}(k) \\
p_{33}^{s_i}(k) &= P_{HPS}^{s_i}(k)
\end{align*}
\]
POSE
High Power Sensing (HPS) State Algorithm

Legend:
- $s_i$: Sensor node $i$
- $P_{HPS}^{s_i}(k)$: Probability that the target is located in HPS coverage area
- $p_{xy}^{s_i}(k)$: State transition probability from state $x$ to state $y$

Set of measurements $z(k)$
Previous target state estimates
$\hat{x}^{s_i}(k-1|k-1)$, $\hat{\Sigma}^{s_i}(k-1|k-1)$

Is State Initialized

State Initialization

Association and State Estimation using JPDA

M-of-N Track Confirmation

One-step Prediction

Validated target state estimates and filter gain matrix
$\hat{x}^{s_i}(k|k)$, $\hat{\Sigma}^{s_i}(k|k)$, $\hat{W}^{s_i}(k|k)$

Information Received

Joint Estimates of Targets

Distributed Fusion

Compute $P_{HPS}^{s_i}(k)$

Legend:
- $s_i$: Sensor node $i$
- $P_{HPS}^{s_i}(k)$: Probability that the target is located in HPS coverage area
- $p_{xy}^{s_i}(k)$: State transition probability from state $x$ to state $y$
POSE
High Power Sensing (HPS) State Algorithm

Joint Probabilistic Data Association (JPDA) Filter [1]

Advantages:
• Updates multiple state estimates at once
• Associates measurements to a previous track
• State may not be corrupted by clutter measurements

Set of HPS Measurements:
\( z(k) \)

Previous state estimates:
\( \hat{x}^{s_i}(k-1|k-1) \)

Previous covariance estimates:
\( \hat{\Sigma}^{s_i}(k-1|k-1) \)

Association and State Estimation using JPDA

Updated state estimates:
\( \hat{x}^{s_i}(k|k) \)

Updated covariance estimates:
\( \hat{\Sigma}^{s_i}(k|k) \)

POSE
High Power Sensing (HPS) State Algorithm

Track Confirmation

\( M \) out of \( N \) consecutive measurements must associate to a track [1]

Benefits

- Allows for Track-before-detect
- Reduced False Tracks generated by False Alarms and Clutter

Legend:

- \( s_i \): Sensor node \( i \)
- \( P_{HPS}^{s_i}(k) \): Probability that the target is located in HPS coverage area
- \( p_{xy}^{s_i}(k) \): State transition probability from state \( x \) to state \( y \)

POSE

High Power Sensing (HPS) State Algorithm

Legend:
\( s_i \): Sensor node \( i \)
\( P_{HPS}^s(k) \): Probability that the target is located in HPS coverage area
\( p_{xy}^{si}(k) \): State transition probability from state \( x \) to state \( y \)
POSE
High Power Sensing (HPS) State Algorithm

Form the Trustworthy Information Ensemble, $\hat{I}_T^s(k)$

Advantages:
- Elimination of faulty/poor state estimates
- Minimize false tracks transmitted by neighbors
- Enhanced state estimation and fusion
- Reduced computational complexity

Received information ensemble:
$\hat{I}^s_i(k) = \{(\hat{x}^{s_j}, \hat{\Sigma}^{s_j}, \hat{W}^{s_j}), \forall s_j \in N_{HPS}^s\}$

Trustworthy Set Formation

Trustworthy information ensemble:
$\hat{I}_T^s(k) = \{(\hat{x}^{s_j}, \hat{\Sigma}^{s_j}, \hat{W}^{s_j}), \forall s_j \in N_T^s\}$

$\hat{I}_T^s(k)$ is computed as follows:
1. The set of trustworthy neighbors $N_T^s \subseteq N_{HPS}^s$ is obtained as follows:
   
   $N_T^s = \{s_j \in N_{HPS}^s : \text{Trace}(H\hat{\Sigma}^{s_j}H') \leq \xi\}$

2. Form the set as follows:
   
   $\hat{I}_T^s(k) = \{(\hat{x}^{s_j}, \hat{\Sigma}^{s_j}, \hat{W}^{s_j}), \forall s_j \in N_T^s\}$

Legend:

- $s_i$: Sensor node $i$
- $s_j$: $s_i$'s $j$th neighbor
- $\xi$: Trustworthy threshold
- $\hat{x}^{s_j}(k|k)$: Target state estimate
- $\hat{\Sigma}^{s_j}(k|k)$: Target covariance estimate
- $\hat{W}^{s_j}(k|k)$: Filter gain matrix
- $H$: Jacobian of measurement matrix
- $N_{HPS}^s$: Set of neighbors who transmitted target state information

Please see the published paper for detailed descriptions of the material.
**POSE**

High Power Sensing (HPS) State Algorithm

**Legend:**
- $s_i$: Sensor node $i$
- $P_{HPS}^s(k)$: Probability that the target is located in HPS coverage area
- $p_{xy}^s(k)$: State transition probability from state $x$ to state $y$
POSE
High Power Sensing (HPS) State Algorithm

Associate and Fuse Trustworthy Information Ensembles using Track-to-track Association and Fusion [1]

Advantages:
• Improves state estimation
• Identifies the number of disjoint tracks
• Incorporates correlation between nodes

Trustworthy information ensemble:
\[ \tilde{I}_T^i(k) = \{(\tilde{x}^s_j, \tilde{\Sigma}_s^j, \tilde{W}_{s_j}), \forall s_j \in \mathcal{N}_T^i \} \]

\[ \mathcal{C} \text{ Associated Trustworthy Information Ensembles} \]

\[ \mathcal{C} \text{ Fused State Estimates} \]

\[ \hat{x}^{i,1}_T(k|k), \hat{\Sigma}^{i,1}_T(k|k) \]
\[ \hat{x}^{i,2}_T(k|k), \hat{\Sigma}^{i,2}_T(k|k) \]
\[ \vdots \]
\[ \hat{x}^{i,C}_T(k|k), \hat{\Sigma}^{i,C}_T(k|k) \]


Please see the published paper for detailed descriptions of the material.
POSE
High Power Sensing (HPS) State Algorithm

Legend:
- $s_i$: Sensor node $i$
- $P_{HPS}^{s_i}(k)$: Probability that the target is located in HPS coverage area
- $p_{xy}^{s_i}(k)$: State transition probability from state $x$ to state $y$

Set of measurements $z(k)$
Previous target state estimates $\hat{x}^{s_i}(k-1|k-1), \tilde{\Sigma}^{s_i}(k-1|k-1)$

Is State Initialized

State Initialization

Association and State Estimation using JPDA

$M$-of-$N$ Track Confirmation

Validated target state estimates and filter gain matrix $\hat{x}^{s_i}(k|k), \tilde{\Sigma}^{s_i}(k|k), \tilde{W}^{s_i}(k|k)$

Information Received

Distributed Fusion

Joint Estimates of Targets

One-step Prediction

Compute $P_{HPS}^{s_i}(k)$

$p_{31}^{s_i}(k) = 0$

$p_{32}^{s_i}(k) = 1 - P_{HPS}^{s_i}(k)$

$p_{33}^{s_i}(k) = P_{HPS}^{s_i}(k)$
**POSE**

**High Power Sensing (HPS) State Algorithm**

One-step Prediction and Computation of $P_{HPS}^{s_i}(k)$

**Advantages:**
- Allows for Opportunistic Sensing
- $s_i$ only transitions to the HPS state if $P_{HPS}^{s_i}(k)$ is high

**Figure:** Visual Representation of $P_{HPS}^{s_i}(k)$

$$ P_{HPS}^{s_i}(k) = \int_D P_{D,HPS}(x, y) \mathcal{N}\left(\hat{x}_i^{s_i}(k + 1|k), \hat{\Sigma}^{s_i}(k + 1|k)\right) dx dy $$

Where:
- $D = \{x, y; ||u^{s_i} - (x, y)|| \leq R_{s,HPS}\}$
- $\hat{x}_i^{s_i}(k + 1|k) = H\hat{x}_i^{s_i}(k + 1|k)$: Predicted target position
- $\hat{\Sigma}_z^{s_i}(k + 1|k) = H\hat{\Sigma}^{s_i}(k + 1|k)H'$: Predicted target position error
**POSE**

**High Power Sensing (HPS) State Algorithm**

- **Legend:**
  - $s_i$: Sensor node $i$
  - $P_{HPS}^{s_i}(k)$: Probability that the target is located in HPS coverage area
  - $p_{xy}^{s_i}(k)$: State transition probability from state $x$ to state $y$

### State Transition Probabilities

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<th>HPS</th>
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<td>$p_{31}^{s_i}$</td>
<td>$0$</td>
<td>$1 - P_{HPS}^{s_i}(k)$</td>
<td>$P_{HPS}^{s_i}(k)$</td>
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### Diagram Explanation:
- **Is State Initialized**: Set of measurements $z(k)$ and previous target state estimates $\hat{x}_{s_i}^{s_i}(k-1|k-1)$, $\hat{\Sigma}_{s_i}^{s_i}(k-1|k-1)$.
- **Association and State Estimation using JPDA**: M-of-N Track Confirmation.
- **M-of-N Track Confirmation**: Validate target state estimates and filter gain matrix $\hat{x}_{s_i}^{s_i}(k|k)$, $\hat{\Sigma}_{s_i}^{s_i}(k|k)$, $\hat{W}_{s_i}^{s_i}(k|k)$.
- **Is Information Received**:
  - Yes: Distributed Fusion.
  - No: One-step Prediction.

#### One-step Prediction:

- Compute $P_{HPS}^{s_i}(k)$:
  - $p_{31}^{s_i}(k) = 0$
  - $p_{32}^{s_i}(k) = 1 - P_{HPS}^{s_i}(k)$
  - $p_{33}^{s_i}(k) = P_{HPS}^{s_i}(k)$
POSE

PFSA Overview

Multi-Modal Sensor Node Control Diagram

✓ Consumes minimal energy
✓ Target detection with LPS devices
✓ Target detection via Distributed Fusion
✓ Uses predictions for control
✓ Performs state estimation
✓ Improves estimation via distributed fusion
✓ Uses predictions for control

Distributed Supervisor Layer

High Power Sensing (HPS) Device (e.g. Laser)
Transmitter/Receiver/GPS

Low Power Sensing (LPS) Device (e.g. PIR)

Data Processing Unit

Sensor Data

LPS \( \theta_1 \)

HPS \( \theta_3 \)

Sleep \( \theta_1 \)

\( p_{11} \)

\( p_{12} \)

\( p_{21} \)

\( p_{23} \)

\( p_{31} \)

\( p_{32} \)

\( p_{33} \)

PIR: Passive Infrared Sensor
POSE

Missed Detection and Energy Characteristics

LPS-HPS Scheme
Distributed detection-based sensor activation

Detection = 1

LPS

Detection = 0

HPS

Random Scheduling Scheme
Distributed probabilistic sensor activation.

Sleep

Sense

1 - prand

1 - prand

POSE Missed Detections

LPS-HPS and RAND
Missed Detections

POSE % Energy Savings
POSE
State Estimation Error Results

Position Root Mean Squared Error

Velocity Root Mean Squared Error

RMS Position Error (m)

RMS Velocity Error (m/s)

Time (s)
The POSE algorithm allows for
- Multi-modal sensor node control,
- Prediction-based Opportunistic Sensing,
- Low missed detection rates,
- Large energy savings, and
- Improved state estimation

POSE Algorithm Limitations
- Redundant sensor nodes tracking
- Target may not be of interest

Theme 2: Prediction-based Opportunistic Sensing using Distributed Classification, Clustering and Control (POSE.3C)
**Main Idea**

**Motivation**

**Types of Targets**
- $c_1$: Target Of Interest (TOI)
- $c_2$: Target Not Of Interest (TNOI)

**Example Applications**
- Humans and Vehicles (TOI) vs. Animals (TNOI) in border surveillance

**Algorithm Improvements:**
- Distributed Classification for opportunistic sensing of TOI
- Distributed Clustering to reduce energy wastage
- Distributed Control

**Legend**
- $R_{S,HPS}$: HPS Sensing Range

---

**Distributed Classification Induced Sensor Selection to enhance tracking TOI**

**Types of Targets**
- $c_1$: Target Of Interest (TOI)
- $c_2$: Target Not Of Interest (TNOI)

**Example Applications**
- Humans and Vehicles (TOI) vs. Animals (TNOI) in border surveillance

**Algorithm Improvements:**
- Distributed Classification for opportunistic sensing of TOI
- Distributed Clustering to reduce energy wastage
- Distributed Control
Objective
Minimize energy consumption by disabling all devices

Description
- Designed to minimize energy consumption when a target is away from the sensor node
- All devices except a clock are disabled
- Once deployed, all sensor nodes start in this state

State Transition Probabilities

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<tr>
<td>( p^{s_i}<em>{11} = p</em>{\text{sleep}} )</td>
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Where \( p_{\text{sleep}} \in [0,1] \) is a design parameter
POSE.3C
Low Power Sensing (LPS) State Algorithm

New Features
➢ Target class decision fusion
➢ Classification induced sensor selection

Legend:
$s_i$: Sensor node $i$
$P_{D,LPS}^{s_i}$: Probability of detection of LPS Device
$P_{HPS}^{s_i}(k)$: Probability that the target is located in HPS coverage area
$S^*$: Set of selected nodes
$p_{xy}^{s_i}(k)$: State transition probability from state $x$ to state $y$

LPS Detect

Distributed Sensor Collaboration

Compute $P_{HPS}^{s_i}(k)$

Distributed Sensor Selection

Distributed Fusion

New Feature

New Feature

Figure: Low Power Sensing State Algorithm
POSE.3C
High Power Sensing (HPS) State Algorithm

- **Sleep**
- **LPS**
- **HPS**

Transition probabilities:
- $p_{11}$
- $p_{12}$
- $p_{21}$
- $p_{22}$
- $p_{23}$
- $p_{31}$
- $p_{32}$
- $p_{33}$
POSE.3C

High Power Sensing (HPS) State Algorithm

Legend:
s_i: Sensor node i
\( \tilde{W}^s_i(k|k) \): Filter gain matrix
\( P_{HPS}^{s_i}(k) \): Probability that the target is located in HPS coverage area
\( S^* \): Set of selected sensors
\( P_{D,LPS}^{s_i} \): LPS Probability of detection
\( p_{x,y}^{s_i}(k) \): State transition probability from state \( x \) to state \( y \)

New Features

➢ Target classification
➢ Target class decision fusion
➢ Classification induced sensor selection

Please see the published paper for detailed descriptions of the material.
POSE.3C
High Power Sensing (HPS) State Algorithm

Legend:
- $s_i$: Sensor node $i$
- $P_{HPS}^{s_i}(k)$: Probability that the target is located in HPS coverage area
- $S^*$: Set of selected sensors
- $P_{D,LPS}^{s_i}$: LPS Probability of detection
- $p_{xy}^{s_i}(k)$: State transition probability from state $x$ to state $y$

Set of measurements $z(k)$

Is State Initialized

State Initialization

Association and State Estimation using JPDA

Previous state estimates $\hat{x}^{s_i}(k-1|k-1)$, $\hat{\Sigma}^{s_i}(k-1|k-1)$

Validated state estimates and filter gain matrix $\hat{x}^{s_i}(k|k)$, $\hat{\Sigma}^{s_i}(k|k)$, $\hat{W}^{s_i}(k|k)$

M-of-N Track Confirmation

Target Classification

Target Class Decision

Is Information Received

Yes

Distributed Fusion

Distributed Sensor Selection

Compute $P_{HPS}^{s_i}(k)$

One-step Prediction

$P_{HPS}^{s_i}(k)$

$s_i \notin S^*$

Compute $P_{HPS}^{s_i}(k)$

$s_i \in S^*$

$p_{31}^{s_i}(k) = 0$

$p_{32}^{s_i}(k) = 1 - P_{D,LPS}^{s_i}$

$p_{33}^{s_i}(k) = P_{HPS}^{s_i}(k)$

$p_{31}^{s_i}(k) = 0$

$p_{32}^{s_i}(k) = 1 - P_{HPS}^{s_i}(k)$

$p_{33}^{s_i}(k) = P_{HPS}^{s_i}(k)$
Target Classification

Validated state estimates:
\( \hat{x}^{s_i}(k|k), \hat{\Sigma}^{s_i}(k|k), \hat{W}^{s_i}(k) \)

Target Class Decision:
\( \hat{D}^{s_i}(k) \)

Validated state estimates:
\( \hat{x}^{s_i}(k|k), \hat{\Sigma}^{s_i}(k|k), \hat{W}^{s_i}(k) \)

Advantages:
- Reduces energy wastage

Target Class Definition:
- \( c_1 \): Target of Interest (TOI)
- \( c_2 \): Target Not Of Interest (TNOI)

Classifier performance is modeled by a Confusion Matrix

\[
\hat{P}_{TOI}^{s_i}(k) = \begin{cases} 
\frac{A}{A + C} & \text{Given } c_1 \\
\frac{C}{C + D} & \text{Given } c_2
\end{cases}
\]

Where:
- \( \hat{D}^{s_i}(k) = 1 \): TOI
- \( \hat{D}^{s_i}(k) = 0 \): TNOI
# POSE.3C

## High Power Sensing (HPS) State Algorithm

### Legend:
- $s_i$: Sensor node $i$
- $P_{HPS}^{s_i}(k)$: Probability that the target is located in HPS coverage area
- $S_{det}$: Set of candidate sensors
- $S_E$: Set of candidates with highest energy remaining
- $S^*$: Set of selected sensors
- $P_{D,LPS}^{s_i} $: LPS Probability of detection
- $p_{xy}(k) $: State transition probability from state $x$ to state $y$

### One-step Prediction

\[
\begin{align*}
    p_{31}^{s_i}(k) &= 1 - P_{D,LPS}^{s_i} \\
    p_{32}^{s_i}(k) &= P_{D,LPS}^{s_i} \\
    p_{33}^{s_i}(k) &= 0
\end{align*}
\]

### New Feature

- Distributed Fusion
- Decision Fusion
- T2T Fusion & Prediction

### New Feature

- Distributed Sensor Selection
- Candidate Identification
- Energy Based Ranking
- GDOP

### Distributed Sensor Collaboration Algorithm

1. **Is State Initialized**
2. **Is State Initialized**
3. **Target Classification**
   - $\tilde{D}_i(k)$
   - $\tilde{x}_i(k|k)$
   - $\tilde{\Sigma}_i(k|k)$
   - $W_i(k|k)$
4. **One-step Prediction**
   - Compute $P_{HPS}^{s_i}(k)$
   \[
   \begin{align*}
    p_{31}^{s_i}(k) &= 0 \\
    p_{32}^{s_i}(k) &= 1 - P_{HPS}^{s_i}(k) \\
    p_{33}^{s_i}(k) &= P_{HPS}^{s_i}(k)
   \end{align*}
   \]
5. **Target Classification**
   - $\tilde{D}_i(k)$
   - $\tilde{x}_i(k|k)$
   - $\tilde{\Sigma}_i(k|k)$
   - $W_i(k|k)$
6. **One-step Prediction**
   - Compute $P_{HPS}^{s_i}(k)$
   \[
   \begin{align*}
    p_{31}^{s_i}(k) &= 0 \\
    p_{32}^{s_i}(k) &= 1 - P_{HPS}^{s_i}(k) \\
    p_{33}^{s_i}(k) &= P_{HPS}^{s_i}(k)
   \end{align*}
   \]
7. **Distributed Fusion**
8. **Distributed Sensor Selection**
9. **Compute $P_{HPS}^{s_i}(k)$**
10. **Update State Estimates**
11. **New Feature**

### Set of measurements $z(k)$
POSE.3C
Distributed Sensor Collaboration Algorithm

Legend:
- \( s_i \): Sensor node \( i \)
- \( P_{HPS}^{s_i}(k) \): Probability that the target is located in HPS coverage area
- \( S_{det} \): Set of sensors that can detect the target
- \( S_E \): Set of sensors with the highest energy remaining
- \( S^* \): Set of selected sensors

Decision Fusion
Fuse associated target class decisions using the Majority Vote.

Benefits
- Forms a single class decision for each target
- Reduces energy wastage via Opportunistic Sensing of Targets Of Interest

\[
\tilde{D}^{s_i,c}(k) = \begin{cases} 
1 & \text{if } \frac{1}{\tilde{l}_{T}^{s_i,c}(k)} \sum_{s_j \in N_T^{s_i,c}} \tilde{D}^{s_j}(k) \geq 0.5 \\
0 & \text{else}
\end{cases}
\]

Where \( \tilde{l}_{T}^{s_i,c}(k) = \{(\tilde{x}^{s_j}, \Sigma^{s_j}, \tilde{W}^{s_j}, \tilde{D}^{s_j}(k))\}, \forall s_j \in N_T^{s_i,c} \) is the set of associated trustworthy information
**POSE.3C**

**Distributed Sensor Collaboration Algorithm**

### Key Features:
- Allows for uniform energy depletion
- Geometric Diversity among HPS nodes
- Classification Driven Clustering

---

**Legend:**
- \( s_i \): Sensor node \( i \)
- \( P_{HPS}^{s_i}(k) \): Probability that the target is located in HPS coverage area
- \( S_{det} \): Set of sensors that can detect the target
- \( S_E \): Set of sensors with the highest energy remaining
- \( S^* \): Set of selected sensors

---

**Distributed Fusion**
- Trustworthy Sets Formation & Data Association
- Decision Fusion
- T2T Fusion & Prediction

**Distributed Sensor Selection**
- Candidate Identification
- Energy Based Ranking
- GDOP

**Compute**
- \( P_{HPS}^{s_i}(k) \)
Candidate Identification
Identify the set of sensors that can detect the predicted target location

\[ S_{det} = \{ s_j \in (N^{s_i} \cup s_i); \| u^{s_j} - H\hat{x}^{s_i}(k + 1|k) \| \leq R_{s,HPS} \} \]

If \( s_i \in S_{det} \), \( s_i \) will broadcast its energy consumed

\[ E^{s_i}_c(k) = \sum_{\kappa=0}^{k} E^{s_i}(\kappa) \]
**POSE.3C**

Distributed Sensor Selection Algorithm

**Candidate Identification**

- $\tilde{D}^{s_i}(k)$
- $\hat{x}^{s_i}(k+1|k)$
- $\hat{\Sigma}^{s_i}(k+1|k)$

**Energy Based Ranking**

Identify the set of sensors with the most energy remaining

1. Rank the sensors in $S_{det}$ by their energy remaining, $E^j_R(k)$

   
   $$E^j_R(k) = 1 - \frac{E^j_c(k) + E_{HPS}}{E_0}$$

   - $E^j_c(k)$: Energy consumption up to time $k$
   - $E_{HPS} = (e_{HPS} + e_{TX} + e_{RX} + e_{DPU})\Delta T$
   - $E_0$: Sensor nodes initial energy

2. Select the top $N'_{sel}$ to form the set $S_E$.

   $$N'_{sel} = \begin{cases} 
   \geq N_{sel} & \text{if } \tilde{D}^{s_i}(k) = 1 \\
   1 & \text{else}
   \end{cases}$$

*Note: $\tilde{D}^{s_i}(k)$ governs the number of selected sensors*
Candidate Identification

Energy Based Ranking

Geometrical Dilution Of Precision (GDOP)

Identify the best set of sensors in $S^*$ that minimizes the predicted measurement covariance error [1].

Identify the set of nodes, $\bar{S}$, that maximizes the cost function $\mu(\bar{S})$

$\mu(\bar{S}) = \frac{\det(J(\bar{S}))}{\text{trace}(J(\bar{S}))}, \quad J(\bar{S}) = \sum_{s_j \in \bar{S}} \frac{1}{\sigma^2_{\phi s_j}} \begin{bmatrix} \sin(\phi_{s_j})^2 & -\sin(\phi_{s_j})\cos(\phi_{s_j}) \\ -\sin(\phi_{s_j})\cos(\phi_{s_j}) & \cos(\phi_{s_j})^2 \end{bmatrix}$

$s.t \; |\bar{S}| = N_{\text{set}} = \left\{ \begin{array}{ll} N_{\text{set}} & \text{if } \tilde{D}^{s_i}(k) = 1 \\ 1 & \text{else} \end{array} \right.$: The desired number of HPS sensors.

Set of Energy Ranked Sensors, $S_F$

Set of Selected Sensors, $S^*$

Legend:
- $s_i$: Sensor node $i$
- $\tilde{D}^{s_i}(k)$: Target class decision
- $\hat{x}^{s_i}(k+1|k)$: Predicted target state estimate
- $\hat{\Sigma}^{s_i}(k+1|k)$: Predicted target covariance estimate
- $N_{\text{set}}$: Desired Number of HPS nodes
- $S^*$: Set of selected sensors

Note: $\tilde{D}^{s_i}(k)$ governs the number of selected sensors

POSE.3C
High Power Sensing (HPS) State Algorithm

Legend:
- \( s_i \): Sensor node \( i \)
- \( P_{HPS}^{s_i}(k) \): Probability that the target is located in HPS coverage area
- \( S^* \): Set of selected sensors
- \( P_{D,LPS}^{s_i} \): LPS Probability of detection
- \( p_{xy}^{s_i}(k) \): State transition probability from state \( x \) to state \( y \)
POSE.3C
PFSA New Features

Multi-Modal Sensor Node Control Diagram

✓ Fuse target class information together
✓ Perform distributed clustering to determine control

✓ Performs target classification

Distributed Supervisor Layer

- High Power Sensing (HPS) Device (e.g. Laser)
- Transmitter/Receiver/GPS

Device Layer

- Low Power Sensing (LPS) Device (e.g. PIR)
- Data Processing Unit

Enabling/Disabling Device Commands

Sensor Data

LPS \( \theta_1 \)

HPS \( \theta_2 \)

Sleep \( \theta_3 \)

\( p_{11} \)

\( p_{12} \)

\( p_{21} \)

\( p_{23} \)

\( p_{31} \)

\( p_{32} \)

\( p_{33} \)

PIR: Passive Infrared Sensor
POSE.3C
Expected Energy Consumption Characteristics

**Theorem 1:** The expected energy consumption of the POSE.3C network during a $\Delta T$ time interval is given as

$$E_{\Delta T}(m) = N_{sel}m\overline{E}_{\Omega_1^1} + (\rho A_{\Omega_1} - N_{sel}m)\overline{E}_{\Omega_1^1'} + \rho A_{\Omega_2}\overline{E}_{\Omega_2} + \rho A_{\Omega_3}\overline{E}_{\Omega_3}$$

- $\rho$: Network Density
- $\overline{E}_{\Omega_1^1} = E_{LPSP2} + E_{HPSP3}$: Expected energy consumption in $\Omega_1^1$
- $\overline{E}_{\Omega_1^1'} = E_{Sleepp1} + E_{LPSP2}$: Expected energy consumption in $\Omega_1^1'$
- $\overline{E}_{\Omega_2} = E_{Sleepp1} + E_{LPSP2} + E_{HPSP3}$: Expected energy consumption in $\Omega_2$
- $\overline{E}_{\Omega_3} = E_{Sleepp1} + E_{LPSP2} + E_{HPSP3}$: Expected energy consumption in $\Omega_3$
- Steady-state probabilities of a node being in each state within each region:

$$
\begin{bmatrix}
p_1^{\Omega_1^1} \\
p_2^{\Omega_1^1} \\
p_3^{\Omega_1^1}
\end{bmatrix} =
\begin{bmatrix}
0 \\
1 - \alpha \\
\alpha 
\end{bmatrix},
\begin{bmatrix}
p_1^{\Omega_1^1'} \\
p_2^{\Omega_1^1'} \\
p_3^{\Omega_1^1'}
\end{bmatrix} =
\begin{bmatrix}
1 - \alpha \\
\frac{2 - \rho_{sleepp} - \alpha}{1 - \rho_{sleepp}} \\
\frac{2 - \rho_{sleepp} - \alpha}{2 - \rho_{sleepp}} \\
0 
\end{bmatrix},
\begin{bmatrix}
p_1^{\Omega_2} \\
p_2^{\Omega_2} \\
p_3^{\Omega_2}
\end{bmatrix} =
\begin{bmatrix}
\frac{1 - \rho_{fa}}{2 - \rho_{sleepp} - \rho_{fa}} \\
\frac{2 - \rho_{sleepp} - \rho_{fa}}{1 - \rho_{sleepp}} \\
\frac{2 - \rho_{sleepp} - \rho_{fa}}{2 - \rho_{sleepp} - \rho_{fa}} \\
0 
\end{bmatrix},
\begin{bmatrix}
p_1^{\Omega_3} \\
p_2^{\Omega_3} \\
p_3^{\Omega_3}
\end{bmatrix} =
\begin{bmatrix}
\frac{1 - 2\rho_{fa}}{2 - \rho_{sleepp} - 2\rho_{fa}} \\
\frac{2 - \rho_{sleepp} - 2\rho_{fa}}{(1 - \rho_{fa})(1 - \rho_{sleepp})} \\
\frac{2\rho_{fa}(1 - \rho_{sleepp})}{2 - \rho_{sleepp} - 2\rho_{fa}} \\
0 
\end{bmatrix}
$$
**POSE.3C**

**Network Lifetime Definition**

**Consider:**
- Multiple targets travel through the network along similar paths
- A path $\Omega_\gamma$ contains the highest frequency of target’s traveling through it
- The number of targets located in $\Omega_\gamma$ during each time step is $\lambda$

**Legend:**
- $L$: Length of the tube $\Omega_\gamma$
- $R_c$: Communication Radius
- $R_{s,HPS}$: HPS Sensing Range
- $\Omega_{1\gamma}$: Region within $R_{s,HPS}$ of targets
- $\Omega_{2\gamma}$: Region within $R_c$ and outside $R_{s,HPS}$ of targets
- $\Omega_{3\gamma}$: Region outside $R_c$ of targets
- $E_0^{s_j}$: Initial energy of node $s_j$
- $E_c^{s_j}$: Energy consumed by node $s_j$
- $\Omega_\lambda$: Region within $R_{s,HPS}$ of targets

**Figure:** Visual Representation of $\Omega_\gamma$ with $\lambda = 2$ targets

**Network Lifetime Definition:** The expected network lifetime, $\bar{T}_{Life}$, is the time when the energy of sensor nodes within $\Omega_\gamma$ reduces to $\eta \in [0,1)$, s.t.

$$\frac{\sum_{s_j \in S_\gamma} \left( E_0^{s_j} - E_c^{s_j}(\bar{T}_{Life}) \right)}{\sum_{s_j \in S_\gamma} E_0^{s_j}} = \eta$$
Theorem 2: The expected lifetime of the POSE.3C network is

\[
\bar{T}_{\text{Life}}(\lambda) = \frac{2\rho R_{s,HPS} L E_0 \Delta T (1 - \eta)}{\bar{E}_{\Delta T}(\lambda)}
\]

- \(\rho\): Network Density
- \(R_{s,HPS}\): HPS device sensing radius
- \(L\): Length of the target track
- \(E_0\): Initial sensor energy
- \(\eta\): Minimum percent of energy tolerated before \(\Omega_\gamma\) is considered dead
- \(\Delta T\): Length of the target track
- \(\lambda\): Expected number of TOI in \(\Omega_\gamma\)
- \(\Omega_\gamma\): A Tube in the deployment region that contains the highest frequency of targets
- \(\bar{E}_{\Delta T}(\lambda)\): Expected energy consumption of the POSE.3C network during a \(\Delta T\) time interval
POSE.3C

Missed Detection Characteristics

**Target Birth:** The time instance when a target appears in the deployment region

**Mature Target:** A target that has travelled inside the region for sufficient time such that sensor collaboration has occurred

**Theorem 3:** The missed detection probability characteristics of a POSE.3C network are given as follows:

a) For a target birth:

\[
P_{m,bir} \geq \exp \left( - \left( \frac{\pi R_r^2 \alpha \chi \rho (1 - p_{sleep})}{2 - p_{sleep} - 2p_{fa}} \right) \right)
\]

b) For a mature target:

\[
P_{m,mat} \geq \exp \left( - \left( \frac{\pi R_r^2 \alpha \chi \rho (1 - p_{sleep}) + \frac{N_{sel}}{\rho \pi R_{s,HPS}^2} (1 - \alpha)}{2 - p_{sleep} - \alpha} \right) \right)
\]

where \( \chi = 1 + \frac{2(1+\beta R_r)}{\beta^2 R_{s,HPS}^2} \left( 1 - \frac{(1+\beta R_{s,HPS}) \exp(-\beta R_{s,HPS})}{(1+\beta R_r) \exp(-\beta R_r)} \right) \)
POSE.3C
Missed Detection Theorem Validation

Theorem 3a Validation: Target Birth

Target Birth $P_m$

Network Density, $\rho \times 10^{-4}$

Theorem 3b Validation: Mature Target

Mature Target $P_m$

Network Density, $\rho \times 10^{-4}$

Simulated
- $P_{sleep} = 0$
- $P_{sleep} = 0.25$
- $P_{sleep} = 0.5$
- $P_{sleep} = 0.75$

Theoretical
- $P_{sleep} = 0$
- $P_{sleep} = 0.25$
- $P_{sleep} = 0.5$
- $P_{sleep} = 0.75$
POSE.3C

Network Lifetime Comparison

Autonomous Node Selection (ANS) [1]
A Distributed Sensor Selection Method that utilizes GDOP as the cost function

LPS-HPS Scheme
Distributed detection-based sensor activation

Random Scheduling Scheme
Distributed Probabilistic sensor activation.

Network Lifetime Normalized by the Lifetime of the POSE.3C Network with $\lambda = 0$

$\lambda$: Expected number of targets
POSE.3C

Estimation Error Comparison

Position Root Mean Squared Error

Velocity Root Mean Squared Error

Legend

- 🌈 ·POSE.C TOI
- ✭ ·POSE.C TNOI
- ▲ ·ANS
- ⭐ ·LPS-HPS
- 🔴 ·RAND, $P_{\text{rand}} = 0$
- 🔴 ·RAND, $P_{\text{rand}} = 0.25$
- 🔴 ·RAND, $P_{\text{rand}} = 0.5$
 Pose.3C

Conclusions and Limitations

The Pose.3C algorithm:
• Distributed classification for opportunistic sensing of TOI
• Distributed clustering for minimizing energy wastage
• Distributed control
• Theoretical properties of energy consumption, network lifetime, missed detections
• Extended the network lifetime
• Accurate state estimation

Pose.3C Algorithm Limitations:
• Does not address multiple co-located node failures
• Network density around target is not used for control

Theme 3: Prediction-based Opportunistic Sensing for Resilience (Pose.R)
Main Idea

Target Coverage

Resilience

➢ Nodes Fail
  ▪ Component degradation, Hardware failures, Malicious attacks, Battery Depletion, etc.
  ▪ Non-uniform Deployment
  ▪ Multiple collocated node failures result in a coverage gap

Proposed Solution

Opportunistically Adjust Sensing Range to fill coverage gaps

Current Adjustable Range Selection Methods
  • Optimize probability of detection while minimizing the number of sensors active
  • Jointly optimize detection and connectivity
  • Optimize network lifetime while ensuring coverage

Research Gaps
  ✓ Resilient target coverage does not exist
  ✓ Only consider stationary targets
  ✓ Do not consider sensor node failures
**POSE.R**

Multi-modal Sensor Node Description

**Figure: Multi-Modal Sensor Node Example**

![Diagram of a multi-modal sensor node with components labeled: Data Processing Unit, Low Power Sensing Device (e.g. PIR), High Power Sensing Device (e.g. Laser), Transmitter/Receiver/GPS.]

### Energy Model

**Individual Sensor node energy consumption** [1,2]:

$$E^{s_i}(k) = \sum_k \sum_j e^{s_i}_j \cdot \chi^{s_i}_j(k) \Delta T + e_{HPS} R^{s_i}_{S,HPS}(k) \chi^{s_i}_{HPS}(k) \Delta T$$

- $e^{s_i}_j$: The rate of energy consumption per unit time of device $j \in \{DPU, LPS, TX, RX, Clock\}$
- $e_{HPS}$: Energy consumption cost of the HPS device
- $\chi^{s_i}_j(k) \in \{0,1\}$: Indicates whether the device is On or Off at time $k$
- $\Delta T$: The sampling interval

**Network energy consumption:**

$$E_{net}(k) = \sum_{i=1}^{n} E^{s_i}(k)$$

- $n$: Number of sensor nodes deployed

---

POSE.R

Main Idea

- Opportunistically turn-on high power sensing on 3 selected sensors around the predicted position of the target and also adjust their sensing ranges to accommodate for low sensing densities and coverage gaps.

Algorithm Improvements:
- Distributed density identification
- Distributed Clustering to ensure $N_{set}$ — coverage degree
- Resilient to sensor failures or sparse deployment

Target Coverage Degree
- Number of nodes covering the target with the HPS devices
**Objective**
Minimize energy consumption by disabling all devices

**Description**
- Designed to minimize energy consumption when a target is away from the sensor node
- All devices except a clock are disabled
- Once deployed, all sensor nodes start in this state

**State Transition Probabilities**

<table>
<thead>
<tr>
<th>Sleep</th>
<th>LPS</th>
<th>HPS</th>
</tr>
</thead>
<tbody>
<tr>
<td>$p_{11}^s = p_{sleep}$</td>
<td>$p_{12}^s = 1 - p_{sleep}$</td>
<td>$p_{13}^s = 0$</td>
</tr>
</tbody>
</table>

Where $p_{sleep} \in [0,1]$ is a design parameter
POSE.R
Low Power Sensing (LPS) State Algorithm

New Features
➢ Adaptive sensor selection for resilient target coverage

Legend:
- $s_i$: Sensor node $i$
- $P_{D,LPS}^s$: Probability of detection of LPS Device
- $P_{HPS}^s(k)$: Probability that the target is located in HPS coverage area
- $S^*$: Set of selected nodes
- $p_{xy}^s(k)$: State transition probability from state $x$ to state $y$

New Feature

Figure: Low Power Sensing State Algorithm
POSE.R
High Power Sensing (HPS) State Algorithm

New Features

- HPS device sensing range may vary based on target location and network density
**POSE.R**

High Power Sensing (HPS) State Algorithm

**Legend:**

- $s_i$: Sensor node $i$
- $p_{HPS}^{s_i}(k)$: Probability that the target is located in HPS coverage area
- $P_{D,LPS}^{s_i}$: LPS device Probability of detection
- $S^*$: Set of selected sensors
- $p_{x,y}^{s_i}(k)$: State transition probability from state $x$ to state $y$

**New Feature**

- Please see the published paper for detailed and updated descriptions of the material.
POSE.R
High Power Sensing (HPS) State Algorithm

Legend:
- $s_i$: Sensor node $i$
- $R^*$: Set of HPS ranges for each selected node
- $N'_{set}$: Number of players for range selection game

Desired Coverage Degree
$N_{set}$
Predicted Target Estimate
$\hat{s}_i (k + 1 | k), \Sigma s_i (k + 1 | k)$
Radius of Candidate Region
$R_{det} = R_1$

EGOP: Energy-based Geometric Dilution Of Precision

Adaptive Sensor Selection

Candidate Identification
Set of Candidate Sensors, $S_{det}$
Set of Selected Sensors, $S^*$
$R_{det} = R_L$
Yes
No
Low Density or Coverage Gap
Adjusts radius of candidate region and desired coverage degree
$R_{det} = R_L, N_{set} = N'_{set}$

EGDOP

Leader Identification
Game Leader
$S_L$
$s_i = s_L$
Yes
No
Wait for Action

Potential Game for Optimal Range Selection

Partition Target Coverage Area

Maxlogit

$S^*$ $N_{set}$-Coverage
$R^*$ Degree is sufficient w/ HPS range $R_1$

Please see the published paper for detailed and updated descriptions of the material.
**POSE.R**

High Power Sensing (HPS) State Algorithm

---

**Adaptive Sensor Selection**

- **Candidate Identification**
  - Identify if node $s_i$ is a candidate for tracking the target

- **EGDOP**
  - Adjusts radius of candidate region and desired coverage degree
  
  $R_{det} = R_L, N_{set} = N_{sel}'$

- **Potential Game for Optimal Range Selection**
  - Game Leader
  - Leader Identification
    - $s_L$
    - $s_I = s_L$
    - Yes
    - Partition Target Coverage Area
    - Yes
    - Maxlogit
    - $S^*$
    - $R^*$

- **Legend:**
  - $s_i$: Sensor node $i$
  - $R^*$: Set of HPS ranges for each selected node
  - $N_{set}'$: Number of players for range selection game

---

Please see the published paper for detailed and updated descriptions of the material.
POSE.R

High Power Sensing (HPS) State Algorithm

Legend:

$s_i$: Sensor node $i$

$R^*$: Set of HPS ranges for each selected node

$N_{set}$: Number of players for range selection game

EGOP: Energy-based Geometric Dilution Of Precision

Desired Coverage Degree $N_{set}$

Predicted Target Estimate $\tilde{x}^k(k+1|k), \Sigma^k(k+1|k)$

Radius of Candidate Region $R_{det} = R_1$

Set of Candidate Sensors, $S_{set}$

Set of Selected Sensors, $S^*$

Potential Game for Optimal Range Selection

Game Leader

Leader Identification

Partition Target Coverage Area

Maxlogit

$S^*$ $N_{set}$-Coverage

$R^*$ Degree is sufficient w/ HPS range $R_1$

Wait for Action

Adjusted radius of candidate region and desired coverage degree $R_{det} = R_L, N_{set} = N'_{set}$

Low Density or Coverage Gap

Adjusted radius of candidate region and desired coverage degree $R_{det} = R_L, N_{set} = N'_{set}$

Yes

No

Yes
POSE.R

High Power Sensing (HPS) State Algorithm

Energy-based Geometrical Dilution Of Precision (EGDOP)

Identify the best set of sensors in $\mathcal{S}^*$ that are geometrically diverse with high energy.

**Process:**

\[
\mu(\mathcal{S}) = \frac{\text{det}(J(\mathcal{S}))}{\text{trace}(J(\mathcal{S}))}, \quad J(\mathcal{S}) = \sum_{s_j \in \mathcal{S}} \frac{E_R^{s_j}}{E_0} \left[ \begin{array}{ccc} \sin(\phi_{s_j})^2 & -\sin(\phi_{s_j})\cos(\phi_{s_j}) & \cos(\phi_{s_j})^2 \\ -\sin(\phi_{s_j})\cos(\phi_{s_j}) & \cos(\phi_{s_j})^2 & \cos(\phi_{s_j}) \\ \cos(\phi_{s_j})^2 & \cos(\phi_{s_j}) & \cos(\phi_{s_j})^2 \end{array} \right]
\]

s.t. $|\mathcal{S}| = N_{sel}$ and

- $E_R^{s_j} = \frac{E_0 - E_{s_j}}{E_0}$: Energy Remaining for sensor node $s_j$
- $\sigma_{\phi,\text{norm}}^2 = \frac{s_{\phi}^2}{4\pi^2}$: Normalized Azimuth Measurement noise
- $r_{s_j,\text{norm}}^2 = \left( \frac{r_{s_j}}{R_{det}} \right)^2$: Normalized Range from the target

**Key difference between EGDOP and GDOP:**
- GDOP minimizes the predicted covariance and does not use energy
- EGDOP scales predicted covariance with energy remaining

Set of Candidate Sensors, $\mathcal{S}_{det}$

Set of Selected Sensors, $\mathcal{S}^*$

Energy Color Code

Max Energy

Min Energy
**POSE.R**

**High Power Sensing (HPS) State Algorithm**

### Adaptive Sensor Selection

**Candidate Identification**
- Desired Coverage Degree $N_{sel}$
- Predicted Target Estimate $\hat{x}^k(k+1|k), \hat{\Sigma}^k(k+1|k)$
- Radius of Candidate Region $R_{det} = R_1$

**EGDOP**
- Set of Candidate Sensors, $S_{det}$
- Set of Selected Sensors, $S^*$

**Game Leader**
- $R_{det} = R_i$
- Yes
- Leader Identification $s_i$
- $s_i = s_i$
- Yes
- Partition Target Coverage Area
- Yes
- Maxlogit $S^*$
- $R^*$

**Potential Game for Optimal Range Selection**

### EGOP:
- Energy-based Geometric Dilution Of Precision

#### Check $R_1$-Coverage Degree

**Insufficient:** $< N_{sel}$ nodes in $S^*$
- Identifies gap/insufficient coverage
- Requires Expanding Candidate Region
- Optimal range selection requires

**Sufficient:** $N_{sel}$ nodes in $S^*$
- Sensor Selection is Complete
- $R^* = \{R_1 | \forall s_j \in S^*\}$

**Legend:**
- $s_i$: Sensor node $i$
- $R^*$: Set of HPS ranges for each selected node
- $N_{sel}$: Number of players for range selection game

Please see the published paper for detailed and updated descriptions of the material.
POSE.R

High Power Sensing (HPS) State Algorithm

Adaptive Sensor Selection

Desired Coverage Degree
\(N_{sel}\)

Predicted Target Estimate
\(\hat{x}^{s_i}(k+1|k), \hat{\Sigma}^{s_i}(k+1|k)\)

Radius of Candidate Region
\(R_{det} = R_1\)

LEGEND:

\(s_i\): Sensor node

\(R^*\): Set of HPS ranges for each selected node

\(N'_{set}\): Number of players for range selection game

EGOP: Energy-based Geometric Dilution Of Precision

Candidate Identification

Set of Candidate Sensors, \(S_{det}\)

Set of Selected Sensors, \(S^*\)

High Density or Coverage Gap

ADJUSTS RADIUS OF CANDIDATE REGION AND DESIRED COVERAGE DEGREE

\(R_{det} = R_L, N_{set} = N'_{set}\)

Low Density or Coverage Gap

Yes

\(|S'| = N'_{set}\)

No

EGDOP

\(R_{det} = R_L\)

No

Yes

Leader Identification

Identify the Game coordinator to identify the players actions.

\(s_L = \arg \max_{s_j} E^s_j\)

Where \(E^s_j\) is the energy remaining of node \(s_j\)

Potential Game for Optimal Range Selection

Game Leader

\(s_L = s_i\)

No

Wait for Action

Partition Target Coverage Area

\(S^*\) Number of players for range selection game

Maxlogit

\(R^*\) Degree is sufficient w/ HPS range \(R_1\)
POSE.R

High Power Sensing (HPS) State Algorithm

Adaptive Sensor Selection

Candidate Identification → EG DOP → Leader Identification → Maxlogit

Desired Coverage Degree
\( N_{sel} \)

Predicted Target Estimate
\( \hat{x}_i(k+1|k), \Sigma_i(k+1|k) \)

Radius of Candidate Region
\( R_{det} = R_1 \)

Legend:

\( s_i \): Sensor node \( i \)

\( R^* \): Set of HPS ranges for each selected node

\( N_{set}' \): Number of players for range selection game

EGOP: Energy-based Geometric Dilution Of Precision

\( |S'| = N_{set} \)

\( R_{det} = R_L, N_{set} = N_{set}' \)

Potential Game for Optimal Range Selection

Game Leader

\( s_L \)

\( s_i = s_L \)

Wait for Action

Partition Target Coverage Area

\( s^* \)

\( N_{set}'\)-Coverage

\( R^* \) Degree is sufficient w/ HPS range \( R_1 \)
**POSE.R Algorithm**

**Potential Game Objective**

**Objective:** Select the optimal sensing range for each node $s_j \in S^*$, s.t.
1. Achieve $N_{sel}$-Coverage, i.e. maximize target coverage
2. Minimize selected sensing range, $R^{s_j}$, i.e. minimize redundant coverage

**Potential Game Preliminaries:**
- **Players:** The set of nodes selected using EGDOP, $S^*$
- **Set of Actions:** Each action, $a_i \in A_i$, represents the nodes sensing range during the next time step, where $A_i = \{R_0, R_1, ..., R_L\}$ is the set of actions or each player and $R_0 = 0m$
- **Utility Function:** $U_i(a_i, a_{-i})$ is the node utility function
- **Potential Function** $\Phi(a_i, a_{-i})$: The global objective function

**Potential Game Requirement:**

$$U_i(a_i', a_{-i}) - U_i(a_i'', a_{-i}) = \Phi(a_i', a_{-i}) - \Phi(a_i'', a_{-i})$$

\[ \forall a_i', a_i'' \in A_i \text{ and } \forall a_{-i} \in A_{-i} \]

**Advantage:**
1. There exists at least one pure-strategy Nash Equilibrium
2. The best equilibrium is the maximizer of the Potential Function
3. There exist learning algorithms, e.g. Maxlogit, that quickly converge to the best equilibrium
4. Fits the distributed framework of the network
**POSE.R Algorithm**

**Sensor Range Selection Game**

### Potential Function Design

\[
\Phi(a) = \sum_{j=1}^{V} \sum_{h=1}^{V} v_{j,h} B_{j,h}(a) - \frac{\sum_{s \in S^*} E_c(a_j)}{|S^*| E_c(R_L)}
\]

- \(v_{j,h}\): Cell worth
- \(B_{j,h}(a)\): Coverage Function
- \(E_c(a_j)\): The energy cost by taking action \(a_j\)

\[
E_c(a_j) = \begin{cases} 
\Delta T \cdot e_{HPS}^s(a_j) & \text{if } a_j \neq R_0 \\
\Delta T \cdot e_{LPS} & \text{if } a_j = R_0
\end{cases}
\]
POSE.R Algorithm

Sensor Range Selection Game

Potential Function Design

\[
\Phi(a) = \sum_{j=1}^{V} \sum_{h=1}^{V} v_{j,h} B_{j,h}(a) - \frac{\sum_{s \in S^*} E_c(a_j)}{|S^*| E_c(R_L)}
\]

- \( v_{j,h} \): Cell worth
- \( B_{j,h}(a) \): Coverage Function
- \( E_c(a_j) \) = \begin{cases} \Delta T \cdot e_{HPS}^s(a_j) & \text{if } a_j \neq R_0 \\ \Delta T \cdot e_{LPS} & \text{if } a_j = R_0 \end{cases}

Achieve \( N_{sel} \)-Coverage, i.e. maximize target coverage

Minimize selected sensing range, \( R^{Si} \), i.e. minimize redundant coverage

Please see the published paper for detailed and updated descriptions of the material.
POSE.R Algorithm

Sensor Range Selection Game

Potential Function Design

\[
\Phi(\alpha) = \sum_{j=1}^{V} \sum_{h=1}^{V} v_{j,h} B_{j,h}(\alpha) - \frac{\sum_{s_j \in S} E_c(a_j)}{|S| E_c(R_L)}
\]

- \(v_{j,h}\): Cell worth
- \(B_{j,h}(\alpha)\): Coverage Function

\[
E_c(a_j) = \begin{cases} 
\Delta T \cdot e_{HPS}(a_j) & \text{if } a_j \neq R_0 \\
\Delta T \cdot e_{LPS} & \text{if } a_j = R_0
\end{cases}
\]
The energy cost by taking action \(a_j\)

Target’s Predicted Position, \(\hat{z}^{sl}(k + 1|k)\)
Target’s Predicted Position Uncertainty, \(\hat{\Sigma}_{z}^{sl}(k + 1|k)\)
Partition Region Cell, \(\Omega_{v,j,h}\)

Cell Worth

\[
v_{j,h} = \frac{\mathcal{N}\left(\left[ x_{j,h}^C, y_{j,h}^C \right]^T, \hat{z}^{sl}(k + 1|k), \hat{\Sigma}_{z}^{sl}(k + 1|k) \right)}{c_1}
\]

- \([x_{j,h}^C, y_{j,h}^C]\): The center points of the cell \(\Omega_{v,j,h}\)
- \(c_1 = \sum_{j=1}^{V} \sum_{h=1}^{V} \mathcal{N}\left(\left[ x_{j,h}^C, y_{j,h}^C \right]^T, \hat{z}^{sl}(k + 1|k), \hat{\Sigma}_{z}^{sl}(k + 1|k) \right):\) Normalization Constant s.t. \(\sum_{j=1}^{V} \sum_{h=1}^{V} v_{j,h} = 1\)
POSE.R Algorithm

Sensor Range Selection Game

Potential Function Design

\[ \Phi(\alpha) = \sum_{j=1}^{V} \sum_{h=1}^{V} v_{j,h} B_{j,h}(\alpha) - \frac{\sum_{s_j \in \mathcal{S}} E_c(a_j)}{|\mathcal{S}| E_c(R_L)} \]

- \( v_{j,h} \): Cell worth
- \( B_{j,h}(\alpha) \): Coverage Function
- \( E_c(a_j) = \begin{cases} \Delta T \cdot e_{\text{HPS}}(a_j) & \text{if } a_j \neq R_0 \\ \Delta T \cdot e_{\text{LPS}} & \text{if } a_j = R_0 \end{cases} \)
  - The energy cost by taking action \( a_j \)

Coverage Function Design

\[ B_{j,h}(\alpha) = \begin{cases} 0.5 \cdot N_{B_{j,h}}(a) & \text{if } N_{B_{j,h}}(a) \leq N_{\text{sel}} \\ 0.5 \left( 6 - N_{B_{j,h}}(a) \right) & \text{if } N_{B_{j,h}}(a) > N_{\text{sel}} \end{cases} \]

- \( N_{B_{j,h}}(a) \): Number of nodes covering cell \( \Omega_{v_{j,h}} \) with joint action \( \alpha \)

Coverage Function Properties

1. The coverage degree of the target’s predicted position is \( N_{\text{sel}} \) if:

   \[ \Delta B_{j,h}(a) \geq \frac{\Delta R}{\chi |\mathcal{S}||R_L}, \forall N_{B_{j,h}}(a) \leq N_{\text{sel}} \]

   \[ \Delta B_{j,h}(a) < \frac{\Delta R}{\chi |\mathcal{S}||R_L}, \forall N_{B_{j,h}}(a) > N_{\text{sel}} \]

   Where \( \Delta B_{j,h}(a) = B_{j,h}(N_{B_{j,h}}(a)) - B_{j,h}(N_{B_{j,h}}(a) - 1) \), and \( \Delta R = R_2 - R_1 \).

2. The total coverage worth achieved by a node \( s_i \)'s best action \( a_i^* \) is:

   \[ \sum_{j=1}^{V} \sum_{h=1}^{V} v_{j,h} \geq 1 - \frac{\Delta R}{\Delta B_{j,h}(a^*) |\mathcal{S}| |R_L|} \]
POSE.R Algorithm
Sensor Range Selection Game
Potential Function Design

$$\Phi(a) = \sum_{j=1}^{V} \sum_{h=1}^{V} v_{j,h} B_{j,h}(a) - \frac{\sum_{s_j \in S^*} E_c(a_j)}{|S^*| E_c(R_L)}$$

- $v_{j,h}$: Cell worth
- $B_{j,h}(a)$: Coverage Function

$$E_c(a_j) = \begin{cases} 
\Delta T \cdot e_{HPS}^s(a_j) & \text{if } a_j \neq R_0 \\
\Delta T \cdot e_{LPS} & \text{if } a_j = R_0 
\end{cases}$$

The energy cost by taking action $a_j$

The normalized energy consumption of the joint action
POSE.R Algorithm

Sensor Range Selection Game

Potential Function Design

\[
\Phi(a) = \sum_{j=1}^{V} \sum_{h=1}^{V} v_{j,h} B_{j,h}(a) - \frac{\sum_{s \in S} E_c(a_j)}{|S^*| E_c(R_L)}
\]

- \( v_{j,h} \): Cell worth
- \( B_{j,h}(a) \): Coverage Function
- \( E_c(a_j) \) = \begin{cases} 
  \Delta T \cdot e_{HPS}^s(a_j) & \text{if } a_j \neq R_0 \\
  \Delta T \cdot e_{LPS} & \text{if } a_j = R_0 
\end{cases}

The energy cost by taking action \( a_j \)

Utility Function Design using Marginal Contribution

\[
U_i(a_i, a_{-i}) = \Phi(a_i, a_{-i}) - \Phi(\emptyset, a_{-i})
\]

\[
U_i(a_i, a_{-i}) = \sum_{j=1}^{V} \sum_{h=1}^{V} v_{j,h} (B_{j,h}(a_i, a_{-i}) - B_{j,h}(R_0, a_{-i})) - \frac{E_c(a_i) - E_c(R_0)}{|S^*| E_c(R_L)}
\]

Proposition 1: The designed utility function results in a Potential Game

Proof:

\[
U_i(a_i', a_{-i}) - U_i(a_i'', a_{-i}) = \Phi(a_i', a_{-i}) - \Phi(\emptyset, a_{-i}) - \Phi(a_i'', a_{-i}) + \Phi(\emptyset, a_{-i})
\]

\[
U_i(a_i', a_{-i}) - U_i(a_i'', a_{-i}) = \Phi(a_i', a_{-i}) - \Phi(a_i'', a_{-i})
\]

\( \square \)
Set of Players $S^*$

Partition Region $\Omega_g$

Cell worth $v_{j,h}$

Maxlogit

Optimal sensing ranges: $R^*$

$R^*$ is found using the Maxlogit Learning Algorithm [1]:

1. Select a Player at random and choose a new action, $a''$, for that player according to a uniform distribution

2. Compute the sensor node utility for the selected player using the previous action $a'_i$ and the new action $a''_i$

3. Compute the deviation probability as follows:

$$\mu = \frac{e^{U_s(a''_i, a_{i-1})}}{\max\left( e^{U_s(a'_i, a_{i-1})}, e^{U_s(a'_i, a_{i-1})} \right)}$$

   - $\tau$: Learning parameter

4. Determine the players next action as follows:

$$a(s_i) = \begin{cases} a'_i & \text{with Pr} = 1 - \mu \\ a''_i & \text{with Pr} = \mu \end{cases}$$

5. Repeat for $N_{iter}$ iterations

---

POSE.R

High Power Sensing (HPS) State Algorithm

Validated state estimates and filter gain matrix

Is State Initialized

State Initialization

Association and State Estimation using JPDA

M-of-N Track Confirmation

Is Information Received

Yes

Distributed Fusion

Adaptive Sensor Selection

Compute $P_{HPS}^s(k)$

No

Distributed Sensor Collaboration

Set of measurements $z(k)$

Previous state estimates $\hat{x}_{si}^k(k-1|k-1), \tilde{\Sigma}_{si}^k(k-1|k-1)$

Legend:

- $s_i$: Sensor node $i$
- $P_{HPS}^s(k)$: Probability that the target is located in HPS coverage area
- $P_{D, LPS}^s$: LPS device Probability of detection
- $S^*$: Set of selected sensors
- $p_{xy}^s(k)$: State transition probability from state $x$ to state $y$

One-step Prediction

$p_{31}^s(k) = 1 - p_{D,LPS}^s$
$p_{32}^s(k) = p_{D,LPS}^s$
$p_{33}^s(k) = 0$

$p_{31}^s(k) = 0$
$p_{32}^s(k) = 1 - P_{HPS}^s(R_{s,HPS}^s(k))$
$p_{33}^s(k) = P_{HPS}^s(R_{s,HPS}^s(k))$

Please see the published paper for detailed and updated descriptions of the material.
POSE.R
PFSA Overview

Multi-Modal Sensor Node Control Diagram

✓ Identifies density around target’s predicted location
✓ Selects optimal sensors and their sensing ranges

✓ Uses Optimal Sensing Range

Distributed Supervisor Layer

High Power Sensing (HPS) Device (e.g. Laser)

Transmitter/Receiver/GPS

Data Processing Unit

Low Power Sensing (LPS) Device (e.g. PIR)

PIR: Passive Infrared Sensor
POSE.R

Characteristics Compared with Existing Techniques

Missed Detection Probability

Avg. Energy Consumption Around Target

Avg. Energy Consumption Away from Target

POSE.R, $p_{\text{sleep}} = 0.5$  
ANS  
LPS-HPS  
RAND, $p_{\text{rand}} = 0$  
RAND, $p_{\text{rand}} = 0.25$  
RAND, $p_{\text{rand}} = 0.5$
POSE.R

Network Lifetime Compared with Existing Techniques

- λ = 0
- λ = 1
- λ = 2
- λ = 3

POSE.R, $p_{\text{sleep}} = 0.5$

ANS

LPS-HPS

RAND, $p_{\text{rand}} = 0$

RAND, $p_{\text{rand}} = 0.25$

RAND, $p_{\text{rand}} = 0.5$
POSE.R

Position Root Mean Squared Error Comparison

Network Density, $\rho = 1.4e^{-3}$
POSE.R

Velocity Root Mean Squared Error Comparison

Network Density, $\rho = 1.4e^{-3}$

- $R_{HPS} = 30\text{m}$
- $R_{HPS} = 36\text{m}$
- $R_{HPS} = 42\text{m}$
- $R_{HPS} = 48\text{m}$
- $R_{HPS} = 52\text{m}$
- $R_{HPS} = 60\text{m}$

Error (m/s)

Time (s)

POSE.R, $p_{\text{sleep}} = 0.5$
- ANS
- LPS-HPS
- RAND, $p_{\text{sleep}} = 0$
- RAND, $p_{\text{sleep}} = 0.25$
- RAND, $p_{\text{sleep}} = 0.5$
Network Resiliency Compared with Existing Techniques

All nodes within a radius $R_{\text{gap}}$ of the targets position at $k = 50s$ have failed.

$R_{\text{gap}}$ was varied between $[30m, 50m]$ for a Network Density $\rho = 1.4e^{-3}$.

**Probability of Detection vs. Time**

- $R_{\text{gap}} = 30$, $R_{\text{HPS}} = 30$
- $R_{\text{gap}} = 40$, $R_{\text{HPS}} = 30$
- $R_{\text{gap}} = 50$, $R_{\text{HPS}} = 30$

**Average Energy Consumption w/in 60m of the targets position vs. Time**

- $R_{\text{gap}} = 30$, $R_{\text{HPS}} = 30$
- $R_{\text{gap}} = 40$, $R_{\text{HPS}} = 30$
- $R_{\text{gap}} = 50$, $R_{\text{HPS}} = 30$

Please see the published paper for detailed explanations of the results.
Network Resiliency Compared with Existing Techniques

All nodes within a radius $R_{\text{gap}}$ of the targets position at $k = 50s$ have failed.

$R_{\text{gap}}$ was varied between $[30m, 50m]$ for a Network Density $\rho = 1.4e^{-3}$
**Objective:** Develop a network autonomy approach that utilizes distributed supervisors (Probabilistic Finite State Automaton) to probabilistically control multi-modal sensor nodes that meets the following requirements:

- Extended network lifetime
- Resilient target coverage
- High tracking accuracy
- Low missed detection rates

**Conclusion**

Please see the published POSE.R paper for results of comparative evaluation of POSE, POSE.3C and POSE.R networks.

**Novel Contributions**

- Distributed Supervisors for probabilistic control of Multi-modal sensor nodes
- Prediction-based Opportunistic Sensing for energy-efficient control
- Distributed Classification for opportunistic sensing of Targets Of Interest
- Distributed Clustering via efficient sensors selection
- Distributed Control
- Prediction-based Opportunistic Coverage
- Resilient target coverage via distributed learning and sensor range adjustment
- Enhanced distributed clustering


**CONFERENCE PUBLICATIONS**


J. Z. Hare, S. Gupta and J. Song, “Distributed Smart Sensor Scheduling for Underwater Target Tracking”, Proceedings of OCEANS’14 MTS/IEEE, St. John’s, Canada, September (2014).


**PATENT SUBMISSIONS**
