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

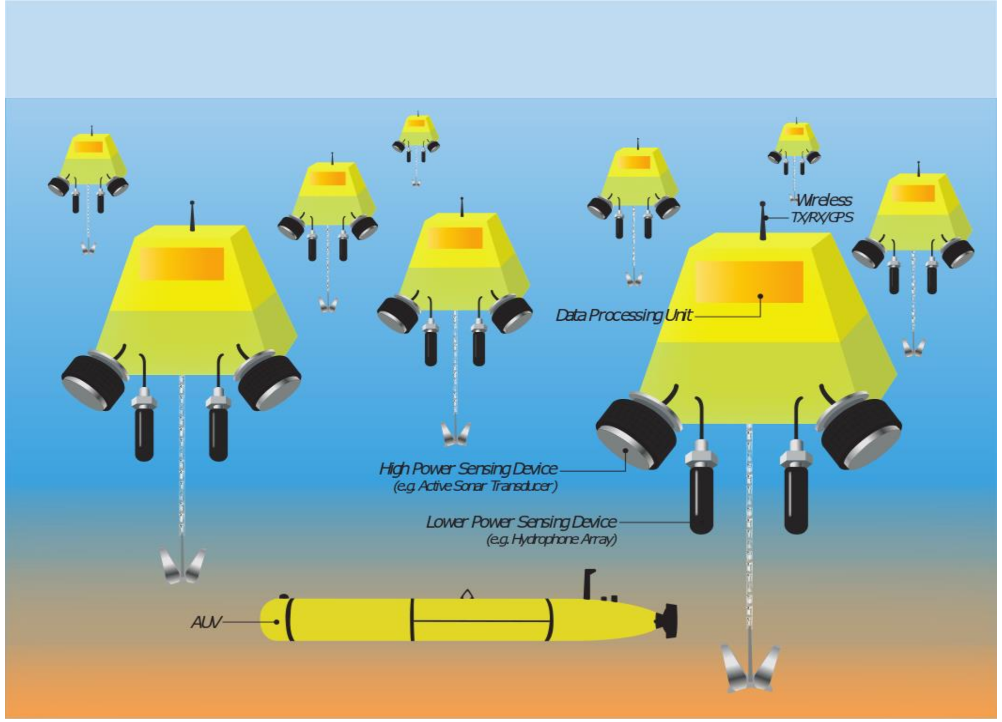


Illustration by Hayley Joyal '18 (SFA)

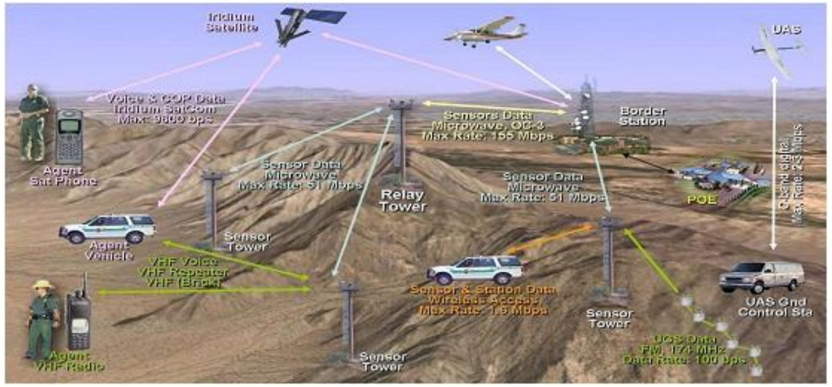
Presented by: James Zachary Hare
Major Advisor: Prof. Shalabh Gupta

Publications below contain detailed updated material.

1) J. Z. Hare, J. Song, S. Gupta and T. A. Wettergren, "POSE.R: Prediction-based Opportunistic Sensing for Resilient and Efficient Sensor Networks", *ACM Transactions on Sensor Networks, accepted 2020,* arXiv:1910.10795
2) J. Z. Hare, S. Gupta and T. A. Wettergren, "POSE.3C: Prediction-based Opportunistic Sensing using Distributed Classification, Clustering and Control in Heterogeneous Sensor Networks", *IEEE Transactions on Control of Network Systems,* Vol. 6, No. 4, pp. 1438-1450, December 2019.
3) J. Z. Hare, S. Gupta and T. A. Wettergren, "POSE: Prediction-based Opportunistic Sensing for Energy Efficiency in Sensor Networks using Distributed Supervisors", *IEEE Transactions on Cybernetics,* Vol. 48, No. 7, pp. 2114-2127, July, 2018.

Intelligent Sensor Networks
Applications

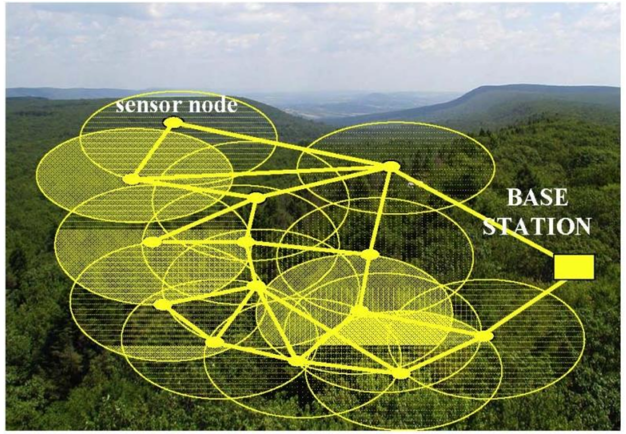
Intelligence, Surveillance, and Reconnaissance



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

"Border Security Strategy Lacks Coherent Operating Concept | Market Info Group LLC - Premium Market & Technology Forecasts." *Market Info Group*. N.p., 03 Nov. 2009. Web. 07 Oct. 2015.

Environmental Monitoring



Example Applications:
- Habitat Monitoring
- Disaster Monitoring

"Wireless Sensor and Actuator Networks." *Automatica, http://automatica.dei.unipd.it/people/schenato/research.html*

Smart Cities and Homes

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

"Top 10 Smart Cities In The World." Stephanie Beaumont, *https://www.linkedin.com/pulse/top-10-smart-cities-world-stephanie-Beaumont,*

Wireless Body Sensor Networks

Example Applications:
- Monitoring Personal Well being
- Activity Monitoring

Yang Zhou, Zhengguo Sheng, Chinmaya Mahapatra, Victor C.M. Leung, Peyman Servati, "Topology design and cross-layer optimization for wireless body sensor networks," *Ad Hoc Networks*, Volume 59, 2017, Pages 48-62,

Intelligent Sensor Networks

Challenges and Current Approaches

UCONN

LINKS
Laboratory of Intelligent Networks and Knowledge-Perception Systems

Objectives

Target Coverage

Energy Efficiency

Resilience

Challenges

- Finite energy resources
- Replacement is difficult

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

Can results in

- Coverage Gaps
- Missed Detections
- Mission Suspension
- Energy Wastage

Solution Approaches

Network Control Architecture

- ❖Centralized
- ❖Cluster-based
- ❖Distributed

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

Research Gaps

- × Typically Centralized or Cluster-based
- × Typically Binary States, either On/Off, and do not consider Multi-modal Sensor Nodes
- × Target Class is not used for Control

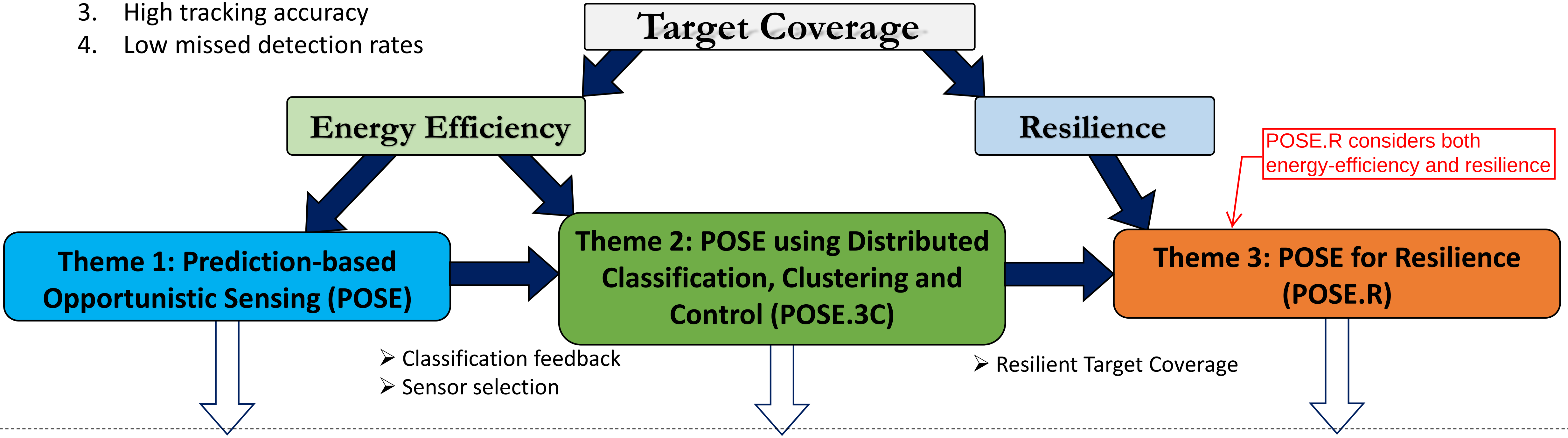
- × Resilient target coverage for stationary networks does not exist
- × Density of target’s predicted location is not used for control

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



- ❑ 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

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

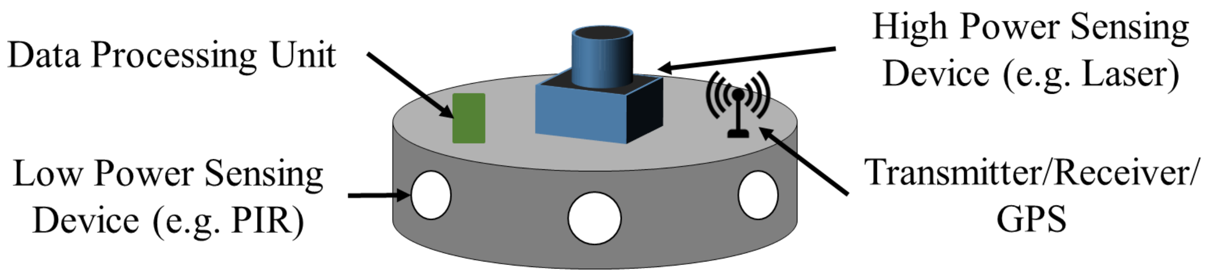


Figure: Multi-modal Sensor Node Example

Energy Model

Individual Sensor node energy consumption [1]:

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

- $e_j^{s_i}$: 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
- ΔT: The sampling interval

Network energy consumption:

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

- n: Number of sensor nodes deployed

[1] J. Chen, K. Cao, K. Li, and Y. Sun, “Distributed sensor activation algorithm for target tracking with binary sensor networks,” *Cluster Computing*, vol. 14, no. 1, pp. 55–64, 2011

Problem Formulation

Target Description

Target Dynamics

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

$$\boxed{\boldsymbol{x}^{\boldsymbol{\tau}}(k+1) = \boldsymbol{f}(\boldsymbol{x}^{\boldsymbol{\tau}}(k), k) + \boldsymbol{v}(k)}$$

- $\boldsymbol{x}^{\boldsymbol{\tau}}(k) = [x, \dot{x}, y, \dot{y}, \phi]'$: Target, τ, state at time k
- $\boldsymbol{f}(\cdot, k)$: State transition matrix, and
- $\boldsymbol{v}(k)$: White noise acceleration sequence with $E[\boldsymbol{v}(k)] = 0$ and $E[\boldsymbol{v}(k)\boldsymbol{v}(k)'] = \boldsymbol{Q}$.

Measurement Models

HPS Device Measurement Model:

$$\boxed{\begin{gathered}\boldsymbol{z}(k) = \left(\boldsymbol{z}_1(k), \ldots, \boldsymbol{z}_m(k)\right) \\ \boldsymbol{z}_j(k) = \boldsymbol{h}(\boldsymbol{x}^{\boldsymbol{\tau}}(k), k) + \boldsymbol{\omega}(k)\end{gathered}}$$

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

LPS Device Measurement Model:

$$\boxed{\boldsymbol{z}(k) \in \{0,1\}}$$

LPS Device Detection Model [2]:

$$\boxed{P_{D,LPS}^{s_i}(k) = \begin{cases} \alpha & ||\boldsymbol{u}^{s_i} - \boldsymbol{u}^{\tau}(k)|| \leq R_r \\ e^{-\beta\left(||\boldsymbol{u}^{s_i} - \boldsymbol{u}^{\tau}(k)|| - R_r\right)} & R_r < ||\boldsymbol{u}^{s_i} - \boldsymbol{u}^{\tau}(k)|| \leq R_{s,LPS} \\ 0 & ||\boldsymbol{u}^{s_i} - \boldsymbol{u}^{\tau}(k)|| > R_{s,LPS} \end{cases}}$$

- α *and* β: Model Design Parameters
- R_r: LPS device reliable sensing range

[1] Bar-Shalom, Yaakov, Peter K. Willett, and Xin Tian. "Tracking and data fusion." *A Handbook of Algorithms. Yaakov Bar-Shalom* (2011).
[2] Y. Zou and K. Chakrabarty, "Sensor deployment and target localization in distributed sensor networks," *ACM Transactions on Embedded Computing Systems*, vol. 3, no. 1, pp. 61–91, 2004.

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:

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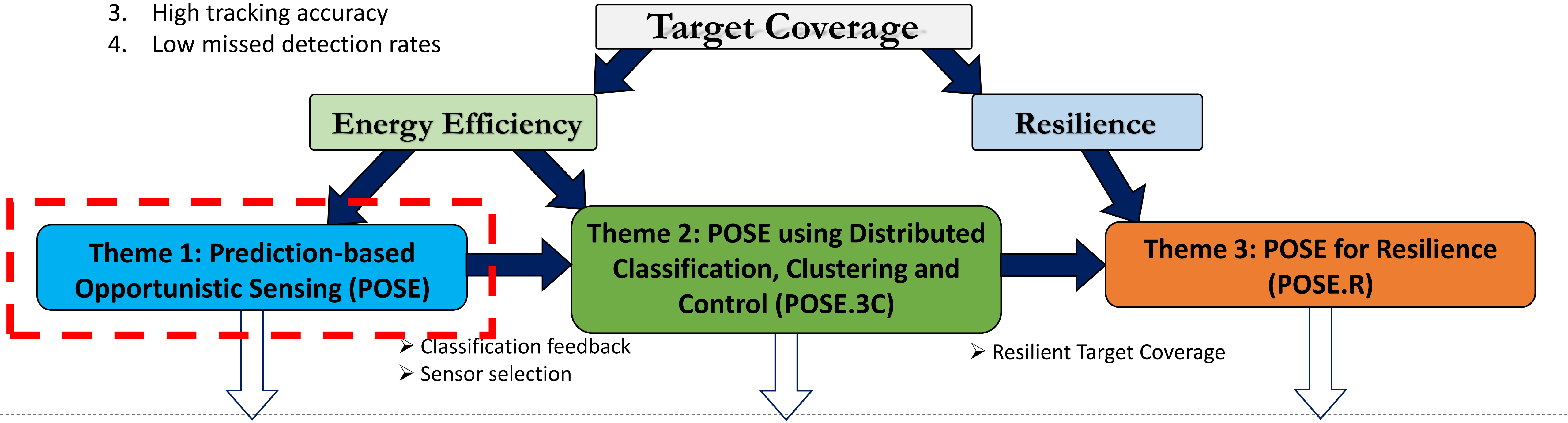

- ❑ Distributed Supervisors for probabilistic control of Multi-modal sensor nodes
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- ❑ Distributed Control

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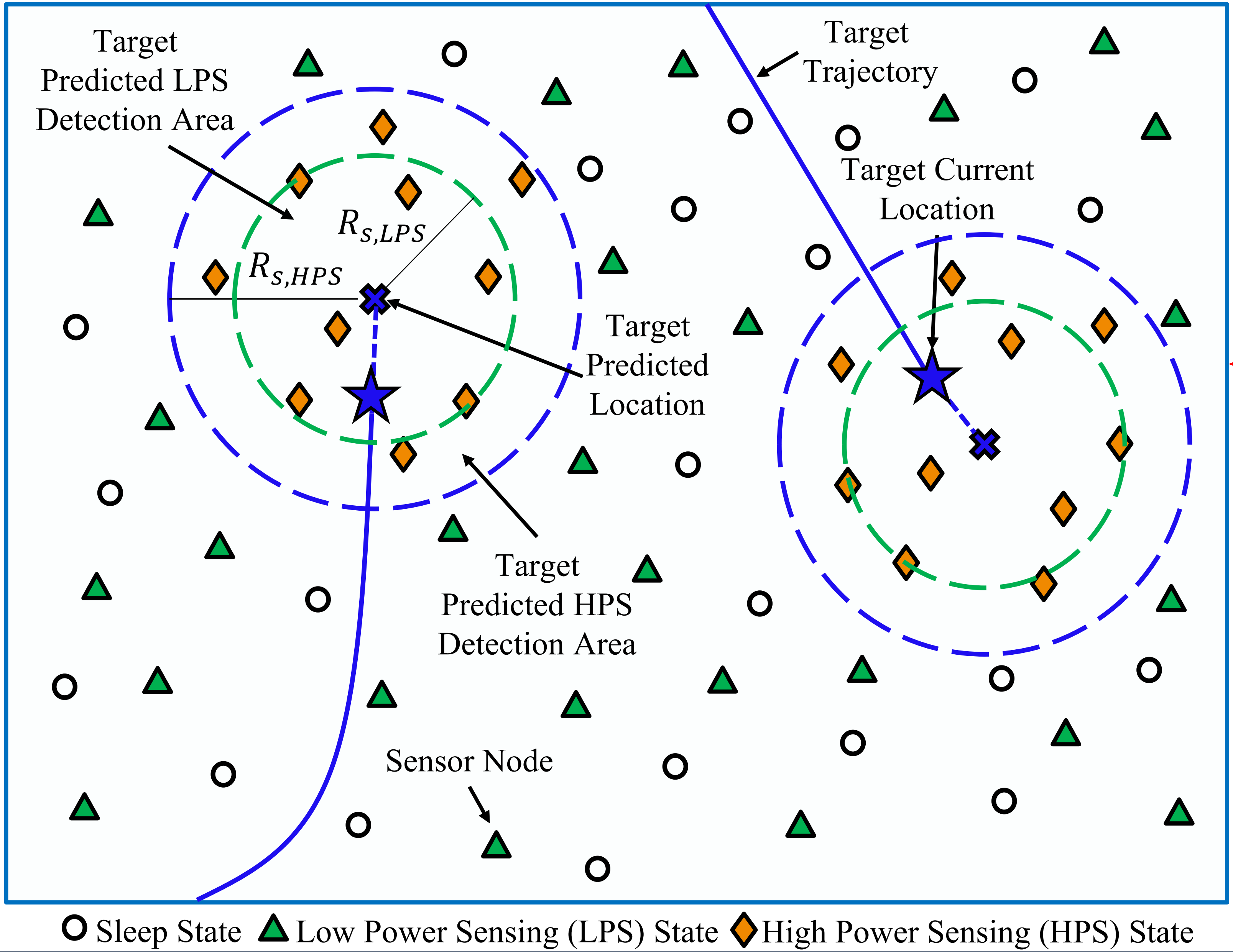
- ❑ Enhanced distributed clustering

Novel Contributions

POSE

Main Idea



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

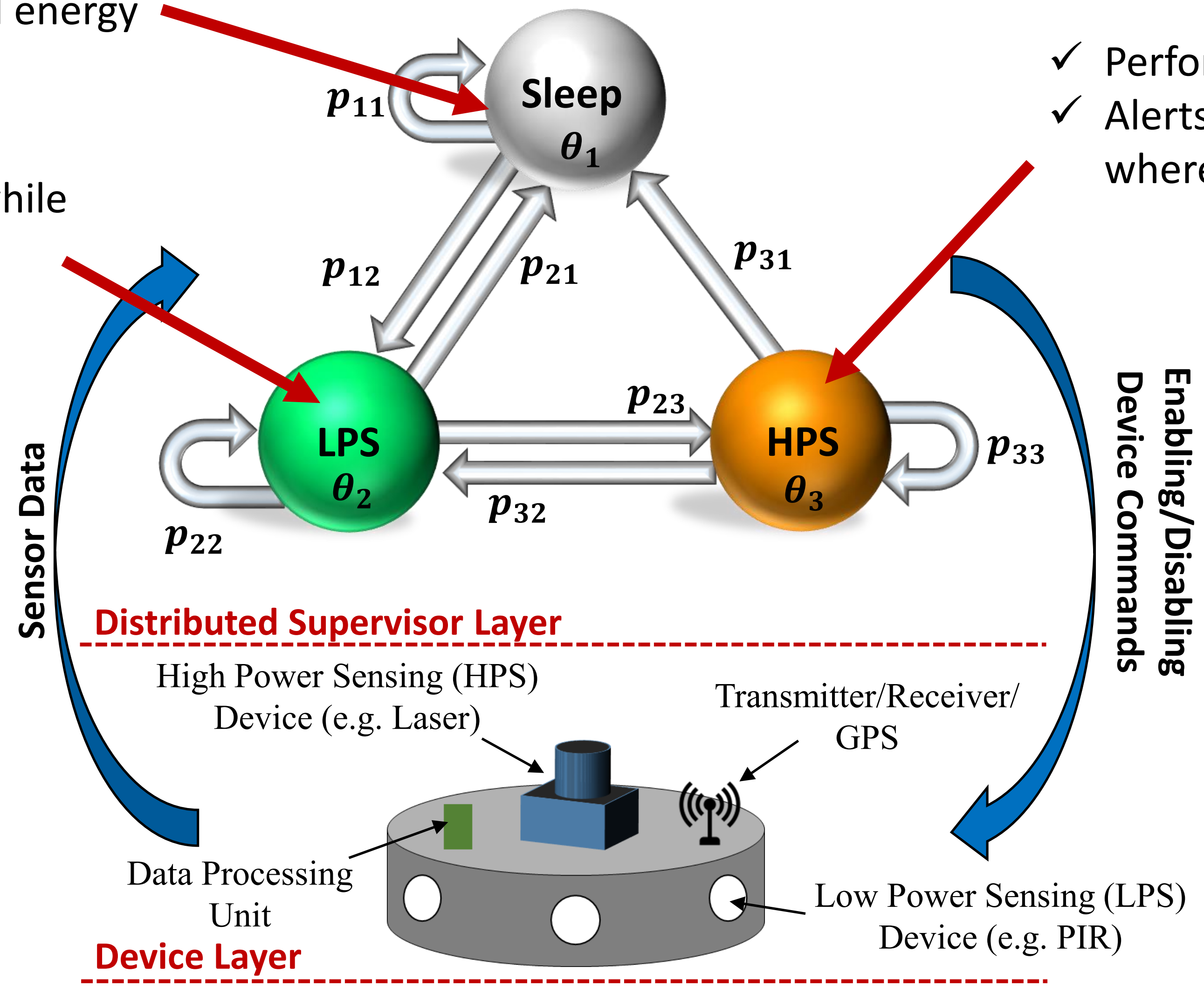
Legend
- $R_{s,LPS}$: LPS Sensing Range
- $R_{s,HPS}$: HPS Sensing Range

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

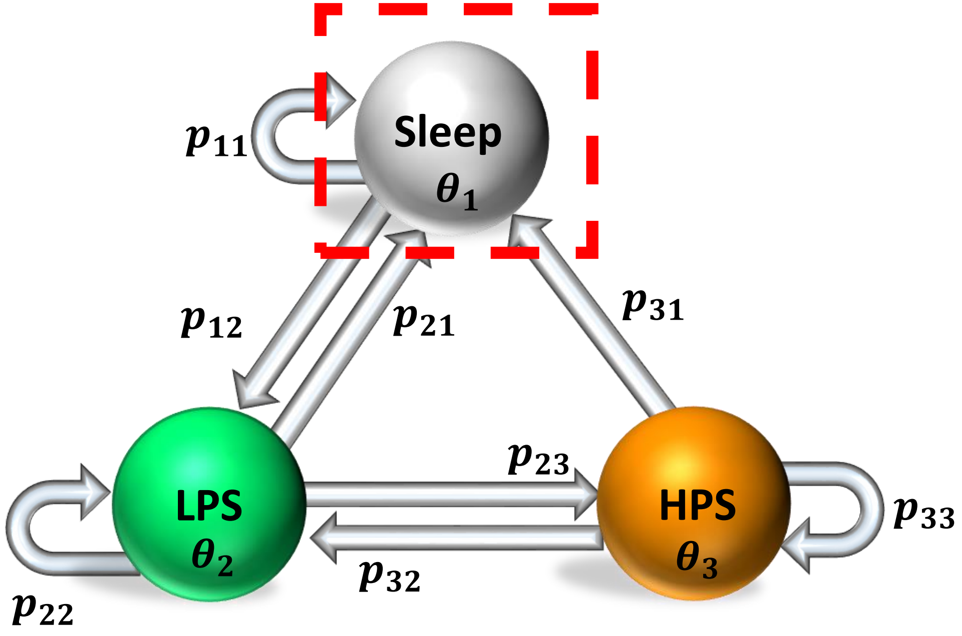


In the published POSE paper we used a 4-state PFSA for distributed control. Here we combined the Listening and LPS states together for compactness and simplicity.

PIR: Passive Infrared Sensor

POSE

Sleep State Algorithm



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

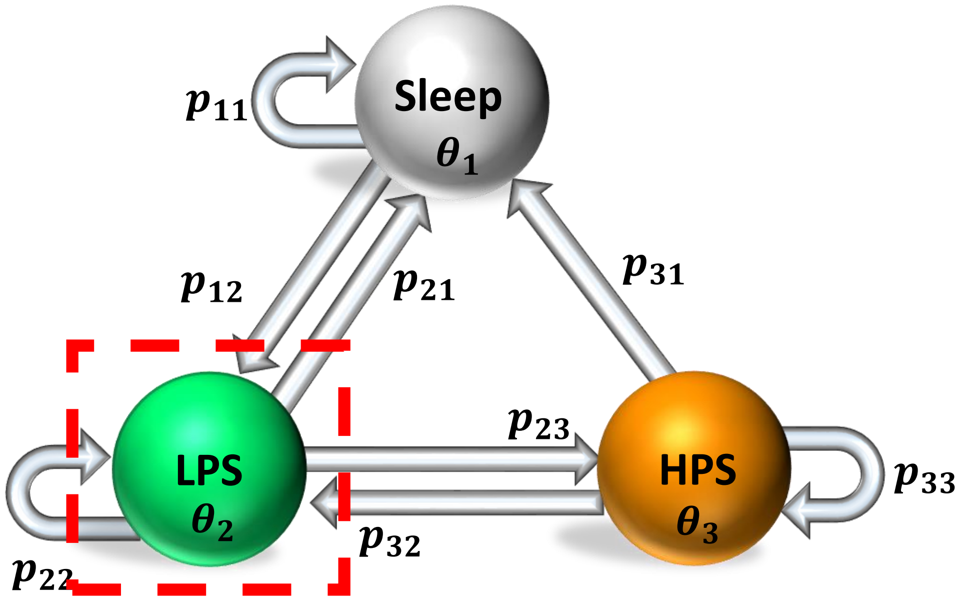
Sleep	LPS	HPS
$p_{11}^{s_i} = p_{sleep}$	$p_{12}^{s_i} = 1 - p_{sleep}$	$p_{13}^{s_i} = 0$

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

LPS: Low Power Sensing
HPS: High Power Sensing

POSE

Low Power Sensing (LPS) State Algorithm



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.

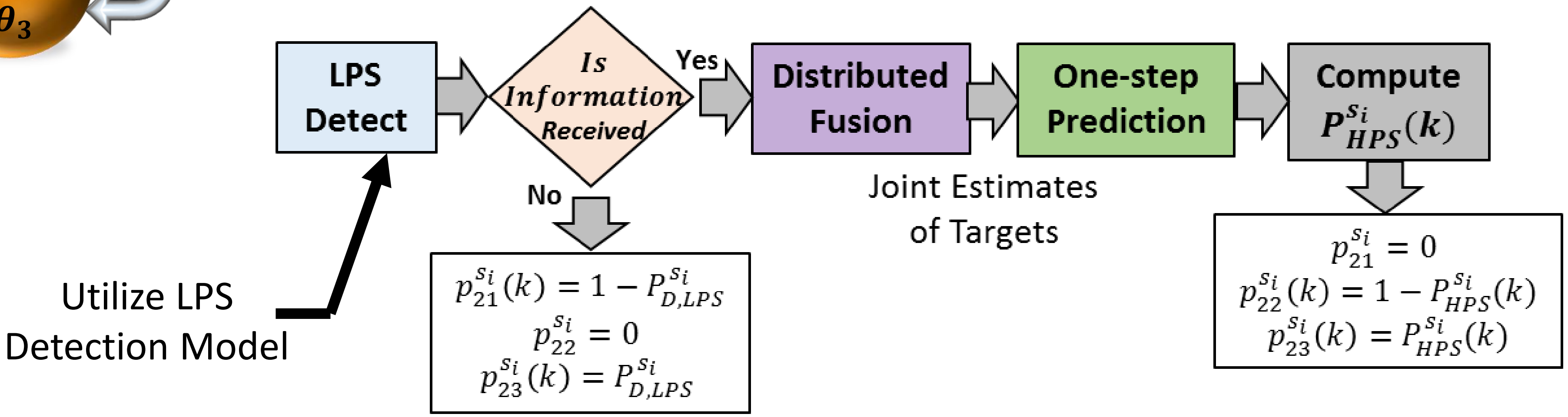


Figure: Low Power Sensing State Algorithm

Legend:

s_i: Sensor node i

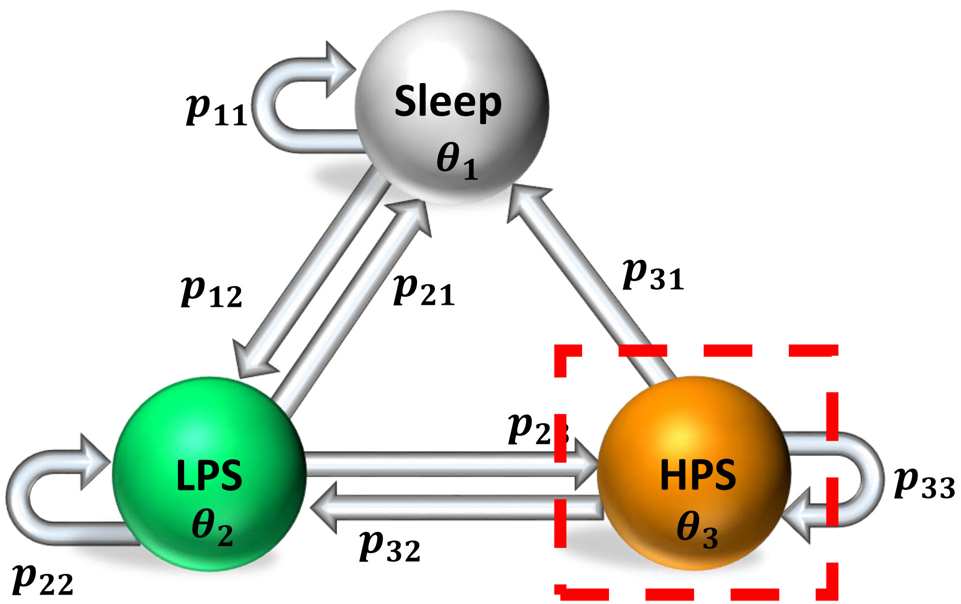
$P_{D,LPS}^{s_i}$: Probability of detection of LPS Device

$P_{HPS}^{s_i}(k)$: Probability that the target is located in HPS coverage area

$p_{xy}^{s_i}(k)$: State transition probability from state x to state y

POSE

High Power Sensing (HPS) State Algorithm



Objective

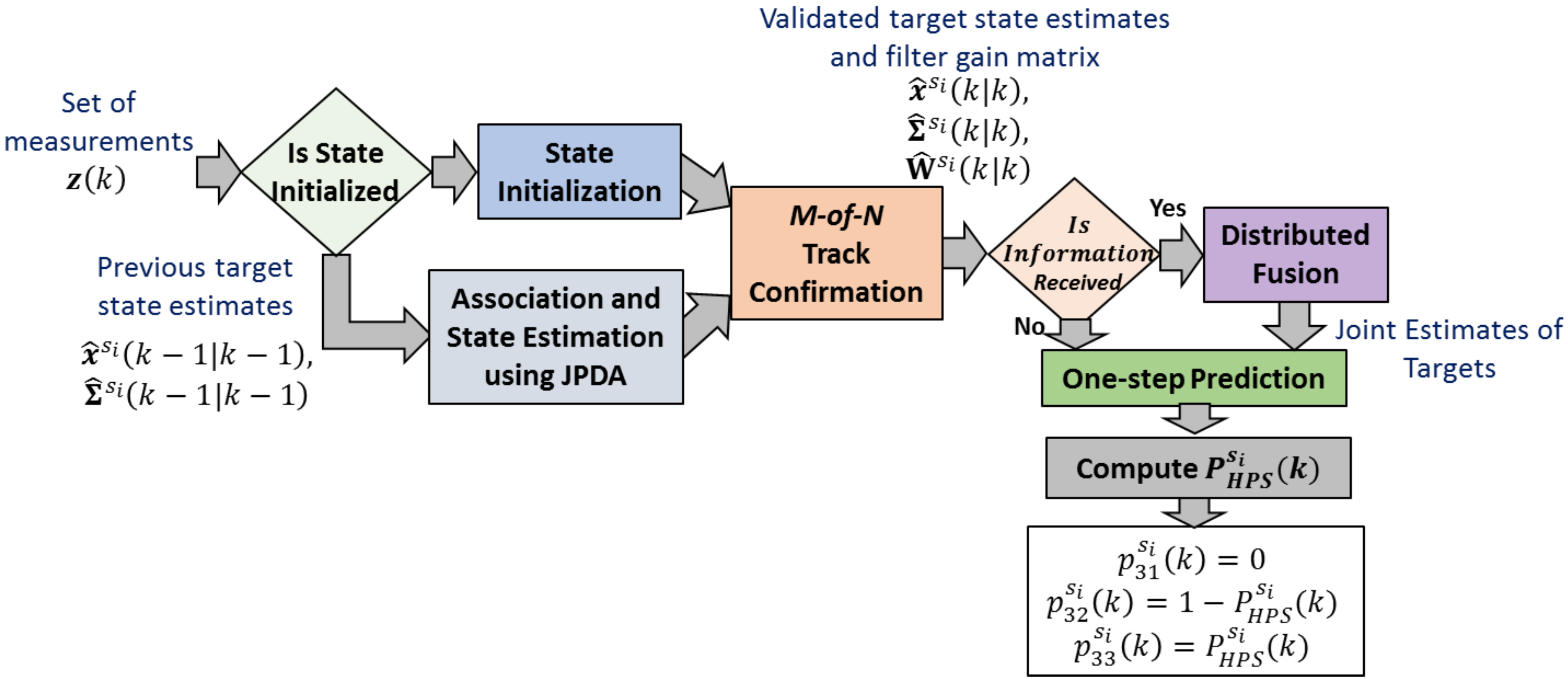
Utilize HPS devices to estimate the target's state and alert neighbors of target's location

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

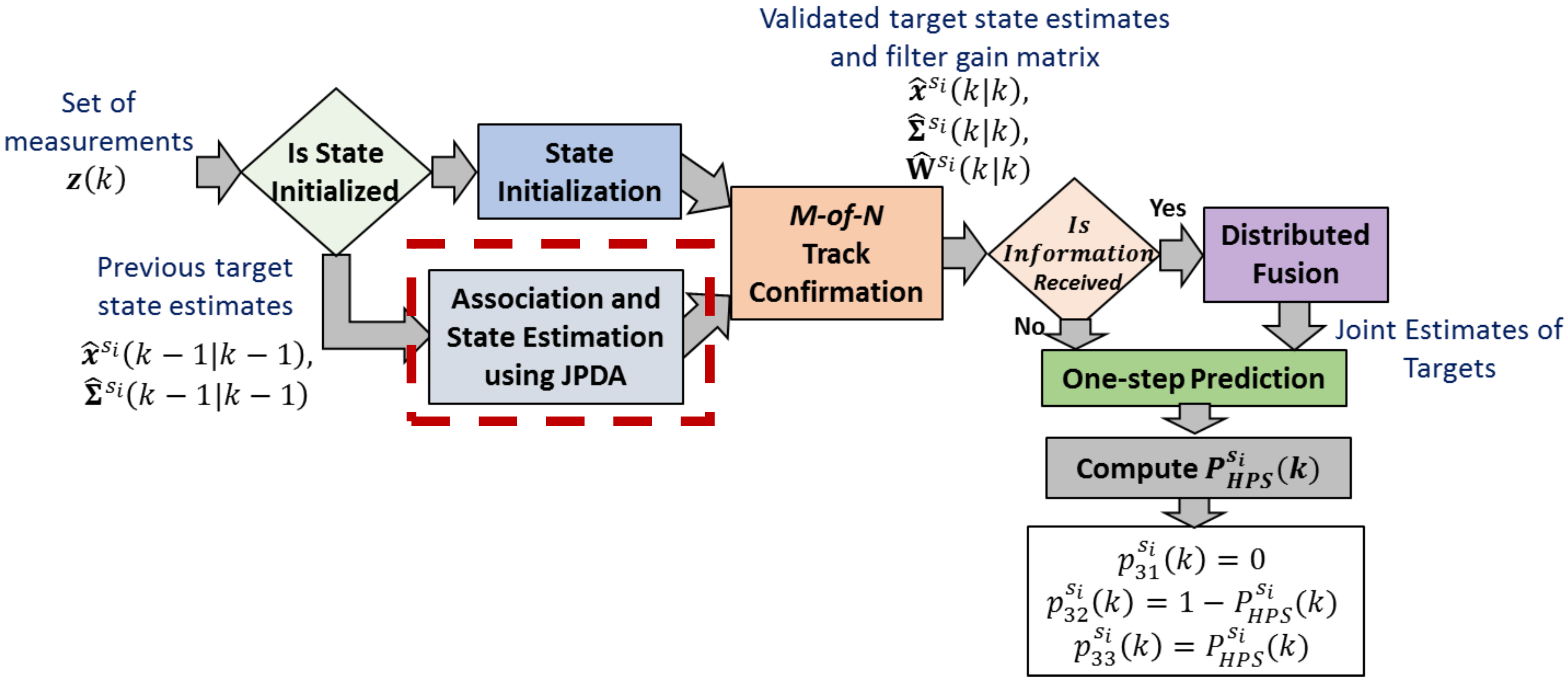
High Power Sensing (HPS) State Algorithm



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

POSE

High Power Sensing (HPS) State Algorithm



<u>Legend:</u>
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: $\boldsymbol{z}(k)$

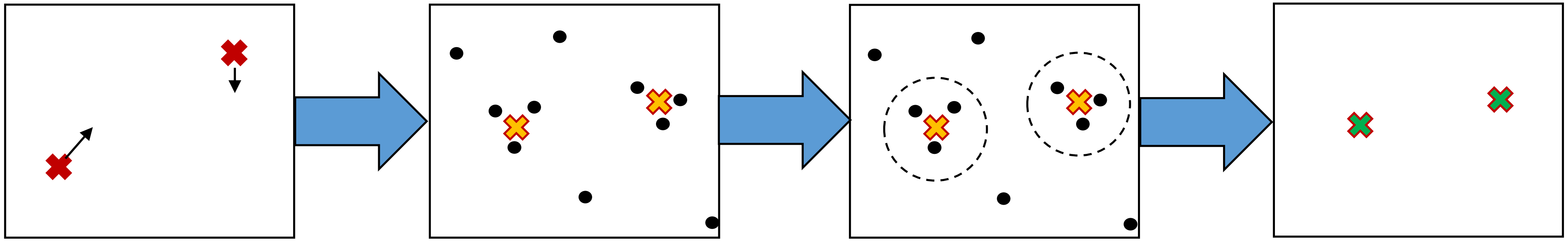
Previous state estimates: $\hat{\boldsymbol{x}}^{s_i}(k-1|k-1)$

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

→ **Association and State Estimation using JPDA** →

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

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

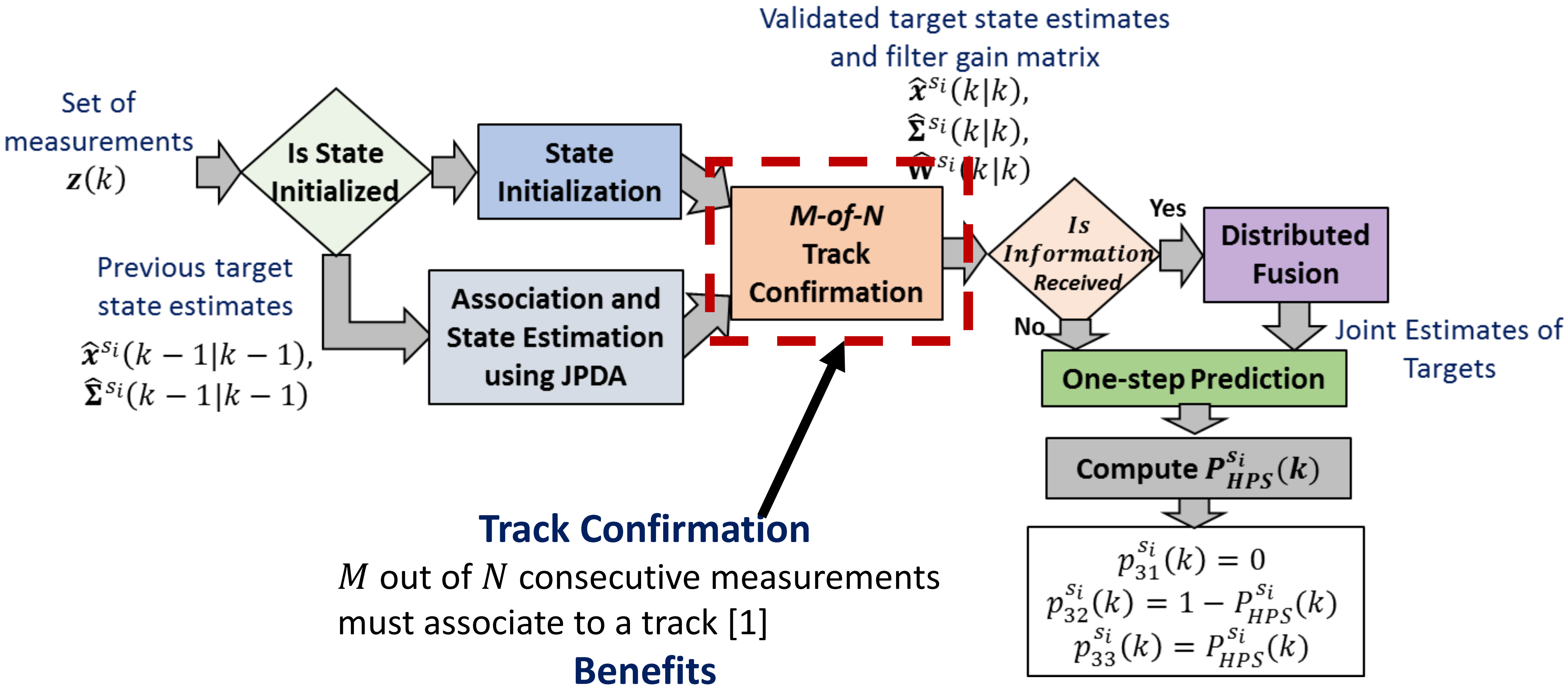


Previous state estimates | **Predicted state estimates and measurement set** | **Associate measurements to estimates** | **Update state estimates**

[1] Y. Bar-Shalom, F. Daum, and J. Huang, “The probabilistic data association filter,” IEEE Control Systems, vol. 29, no. 6, pp. 82–100, 2009.

POSE

High Power Sensing (HPS) State Algorithm



Track Confirmation

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

Benefits

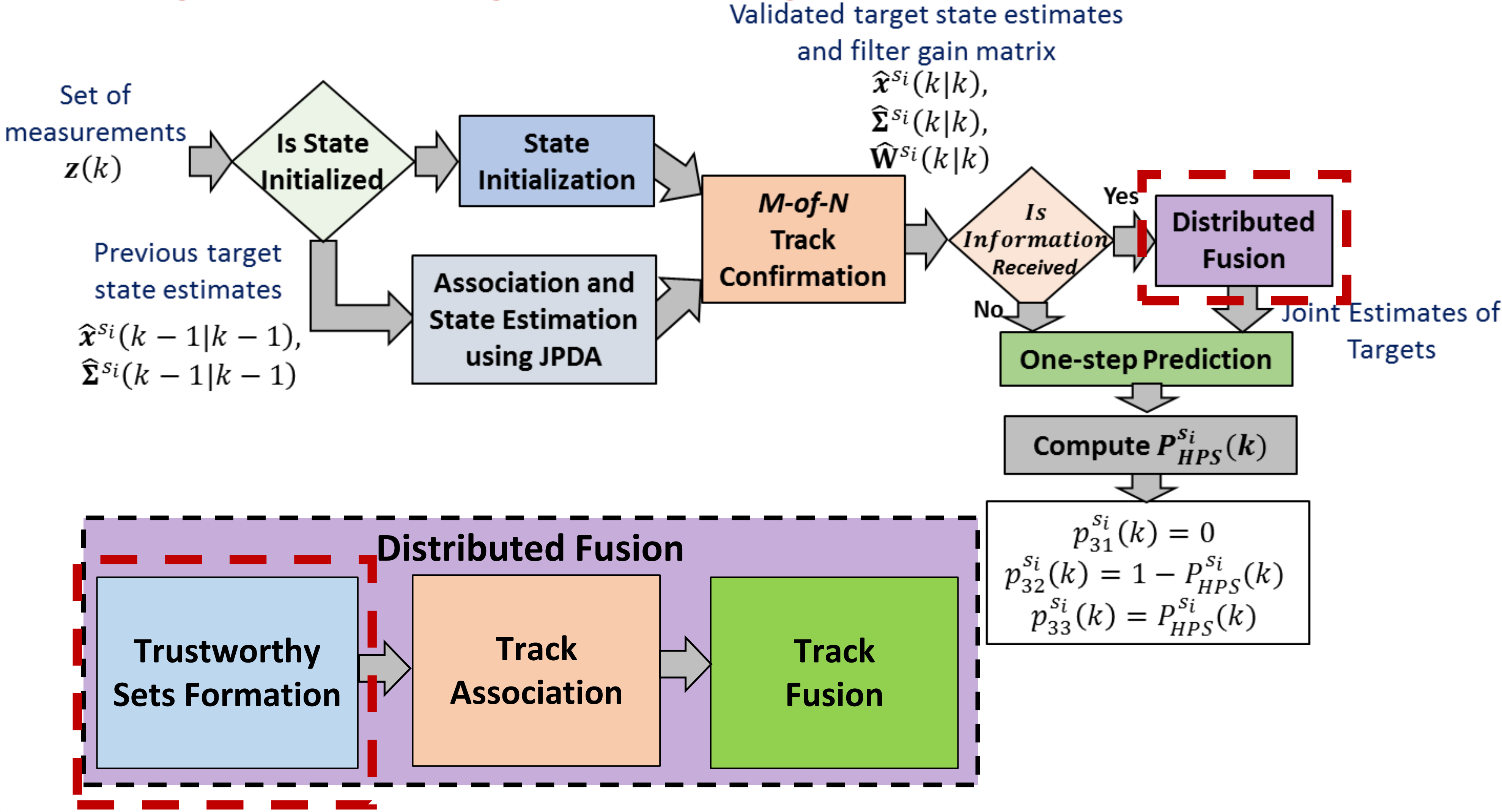
- Allows for Track-before-detect
- Reduced False Tracks generated by False Alarms and Clutter

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

[1] S. Coraluppi and C. Carthel, "Distributed tracking in multistatic sonar," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 41, no. 3, pp. 1138–1147, 2005.

POSE

High Power Sensing (HPS) State Algorithm



<u>Legend:</u>

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

Form the Trustworthy Information Ensemble, $\hat{\boldsymbol{I}}_{\boldsymbol{T}}^{s_i}(k)$

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

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

Received information ensemble:
$\hat{\boldsymbol{I}}^{s_i}(k) = \{(\hat{\boldsymbol{x}}^{s_j}, \hat{\boldsymbol{\Sigma}}^{s_j}, \widehat{\boldsymbol{W}}^{s_j}), \forall s_j \in \mathcal{N}_{HPS}^{s_i}\}$ → **Trustworthy Set Formation** → *Trustworthy information ensemble*:
$\hat{\boldsymbol{I}}_T^{s_i}(k) = \{(\hat{\boldsymbol{x}}^{s_j}, \hat{\boldsymbol{\Sigma}}^{s_j}, \widehat{\boldsymbol{W}}^{s_j}), \forall s_j \in \mathcal{N}_T^{s_i}\}$

$\mathcal{N}_{HPS}^{s_i}$: Set of neighbors who transmitted target state information

$\hat{\boldsymbol{I}}_T^{s_i}(k)$ is computed as follows:

1. The set of trustworthy neighbors $\mathcal{N}_T^{s_i} \subseteq \mathcal{N}_{HPS}^{s_i}$ is obtained as follows:

$$\mathcal{N}_T^{s_i} = \{s_j \in \mathcal{N}_{HPS}^{s_i} : Trace(\boldsymbol{H}\hat{\boldsymbol{\Sigma}}^{s_j}\boldsymbol{H}') \leq \xi\}$$

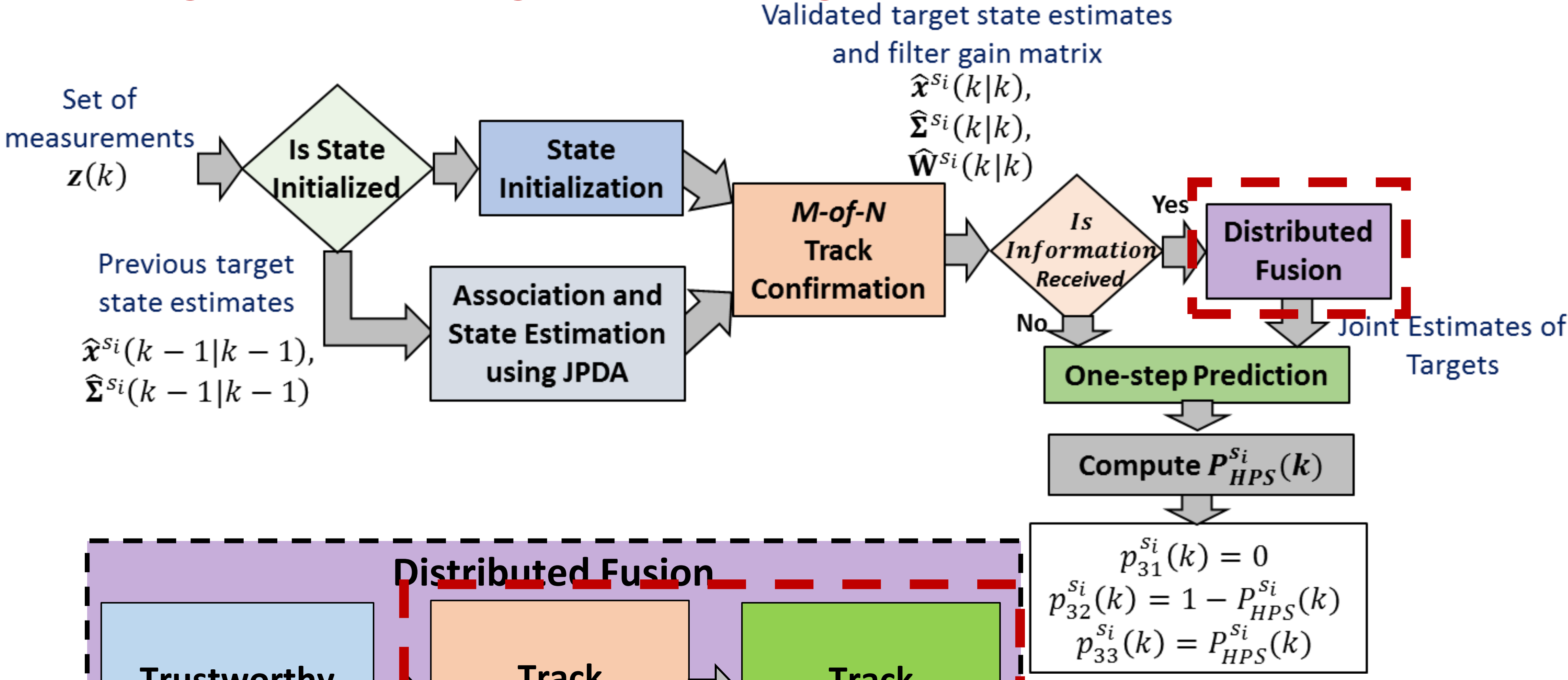
2. Form the set as follows:

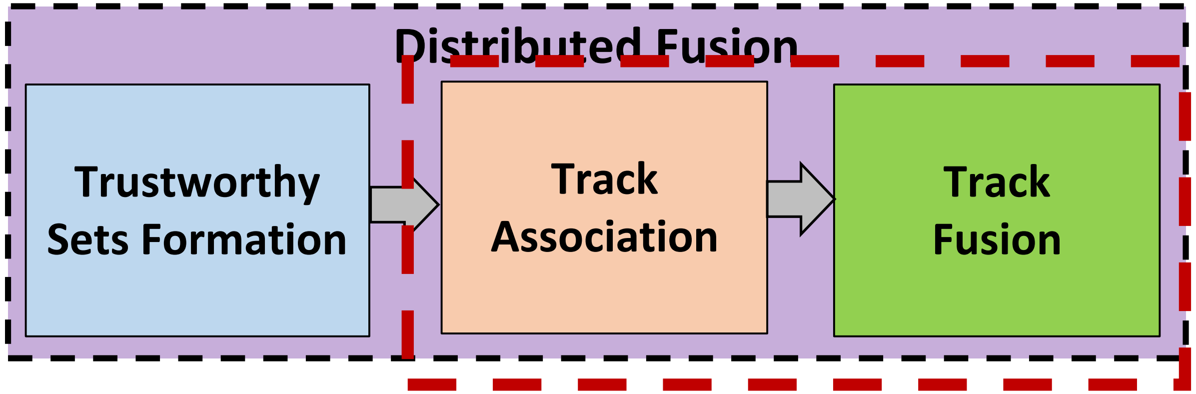
$$\hat{\boldsymbol{I}}_T^{s_i}(k) = \{(\hat{\boldsymbol{x}}^{s_j}, \hat{\boldsymbol{\Sigma}}^{s_j}, \widehat{\boldsymbol{W}}^{s_j}), \forall s_j \in \mathcal{N}_T^{s_i}\}$$

<u>Legend:</u>
s_i: Sensor node i
s_j: s_i's jth neighbor
ξ: Trustworthy threshold
$\hat{\boldsymbol{x}}^{s_j}(k|k)$: Target state estimate
$\hat{\boldsymbol{\Sigma}}^{s_j}(k|k)$: Target covariance estimate
$\widehat{\boldsymbol{W}}^{s_j}(k|k)$: Filter gain matrix
$\boldsymbol{H}$: Jacobian of measurement matrix

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

POSE

High Power Sensing (HPS) State Algorithm

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

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

Advantages:

- Improves state estimation
- Identifies the number of disjoint tracks
- Incorporates correlation between nodes

Trustworthy information ensemble:

$$\hat{\boldsymbol{I}}_T^{s_i}(k) = \left\{\left(\hat{\boldsymbol{x}}^{s_j}, \hat{\boldsymbol{\Sigma}}^{s_j}, \widehat{\boldsymbol{W}}^{s_j}\right), \forall s_j \in \mathcal{N}_T^{s_i}\right\}$$

→ **Track-to-track Association** →

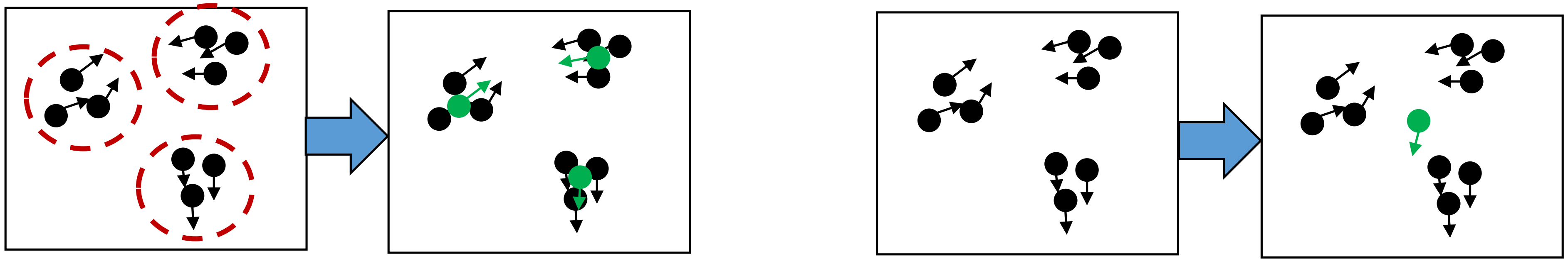
C Associated Trustworthy Information Ensembles

$$\hat{\boldsymbol{I}}_T^{s_i,1}(k), \quad \hat{\boldsymbol{I}}_T^{s_i,2}(k), \quad \vdots \quad \hat{\boldsymbol{I}}_T^{s_i,C}(k)$$

→ **Track-to-track Fusion** →

C Fused State Estimates

$$\hat{\boldsymbol{x}}^{s_i,1}(k|k), \hat{\boldsymbol{\Sigma}}^{s_i,1}(k|k)$$
$$\hat{\boldsymbol{x}}^{s_i,2}(k|k), \hat{\boldsymbol{\Sigma}}^{s_i,2}(k|k)$$
$$\vdots$$
$$\hat{\boldsymbol{x}}^{s_i,C}(k|k), \hat{\boldsymbol{\Sigma}}^{s_i,C}(k|k)$$

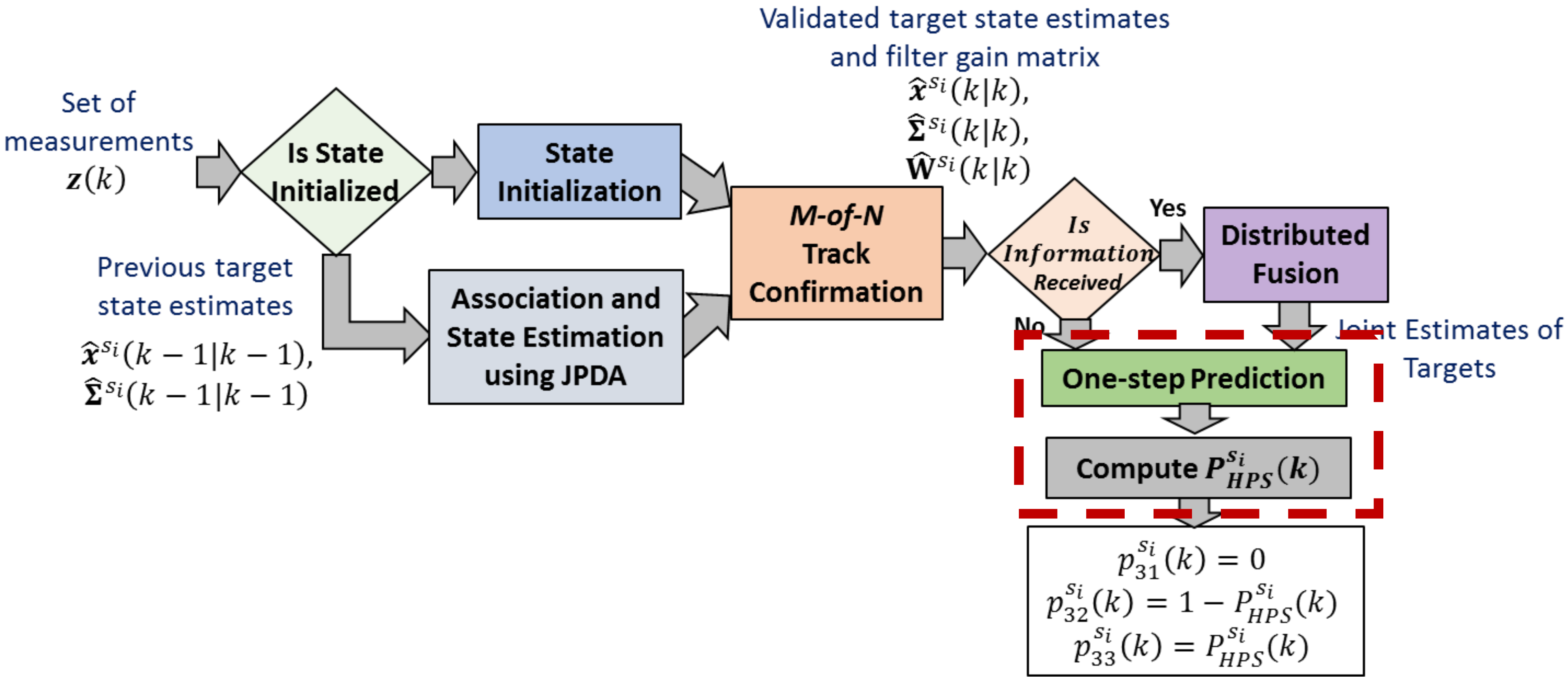


Associated Tracks | **Fused Tracks w/ Association** | **Received Tracks** | **Fused Tracks w/out Association**

[1] Bar-Shalom, Yaakov, Peter K. Willett, and Xin Tian. "Tracking and data fusion." *A Handbook of Algorithms. Yaakov Bar-Shalom* (2011).

POSE

High Power Sensing (HPS) State Algorithm



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

POSE

High Power Sensing (HPS) State Algorithm

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

State estimates: $\hat{\mathbf{x}}^{s_i}(k|k)$

Covariance estimates: $\hat{\mathbf{\Sigma}}^{s_i}(k|k)$

→ **One-step Prediction** →

Predicted State estimates: $\hat{\mathbf{x}}^{s_i}(k+1|k)$

Predicted Covariance estimates: $\hat{\mathbf{\Sigma}}^{s_i}(k+1|k)$

→ **Compute $P_{HPS}^{s_i}(k)$** →

Probability that the target will be located in the HPS coverage area $P_{HPS}^{s_i}(k)$

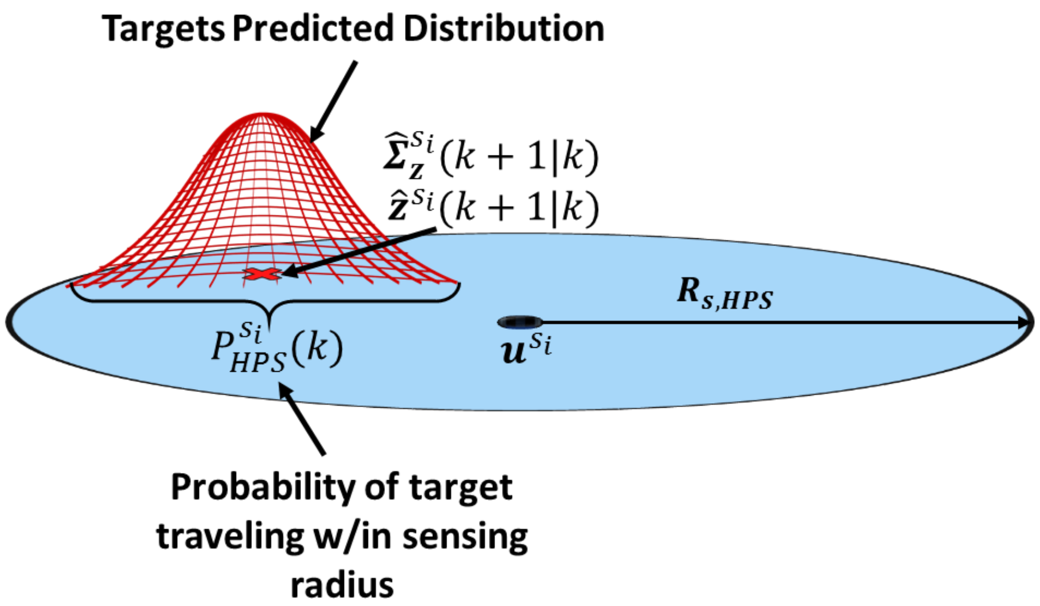


Figure: Visual Representation of $P_{HPS}^{s_i}(k)$

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

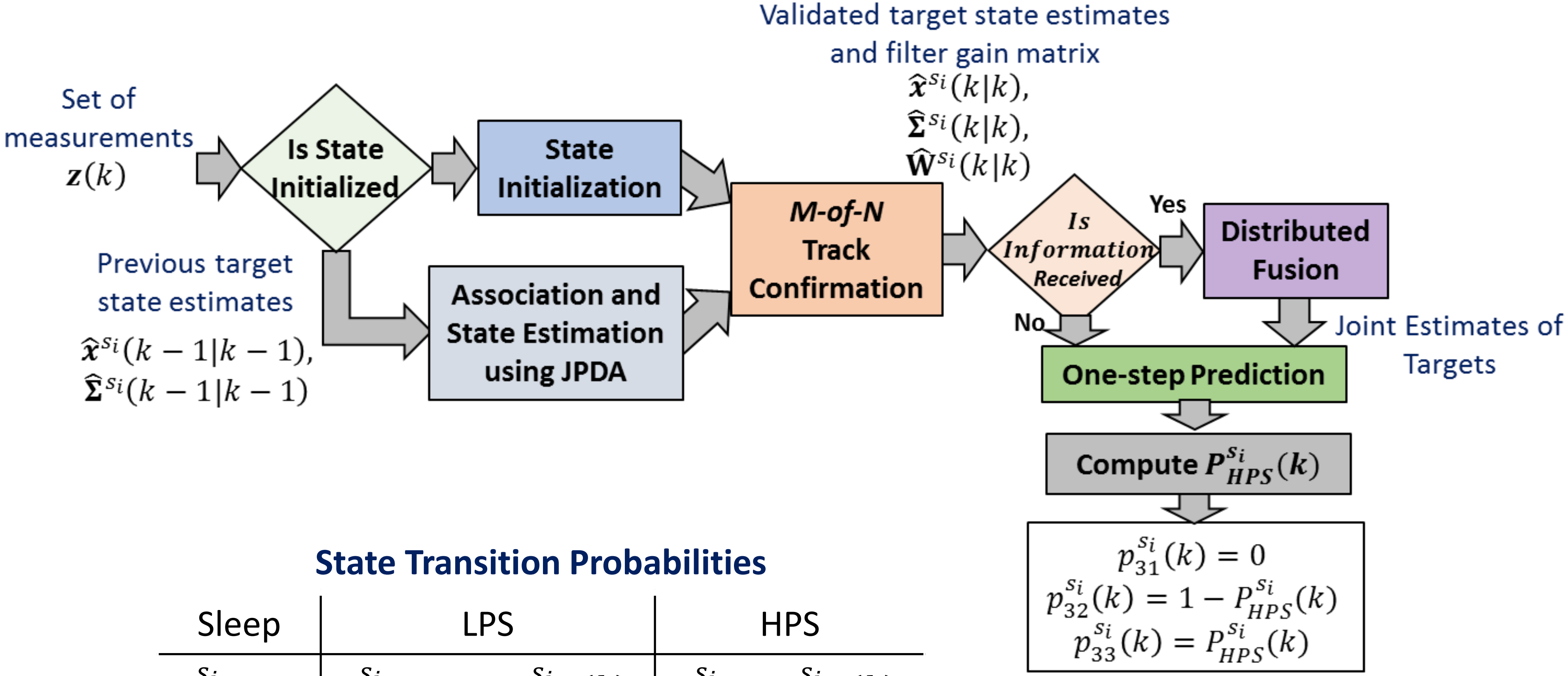
$$P_{HPS}^{s_i}(k) = \iint_D P_{D,HPS}^{s_i}(x,y)\mathcal{N}\left(\hat{\mathbf{z}}^{s_i}(k+1|k), \hat{\mathbf{\Sigma}}_{\mathbf{z}}^{s_i}(k+1|k)\right) dxdy$$

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

$R_{s,HPS}$: HPS device sensing range

POSE

High Power Sensing (HPS) State Algorithm



State Transition Probabilities

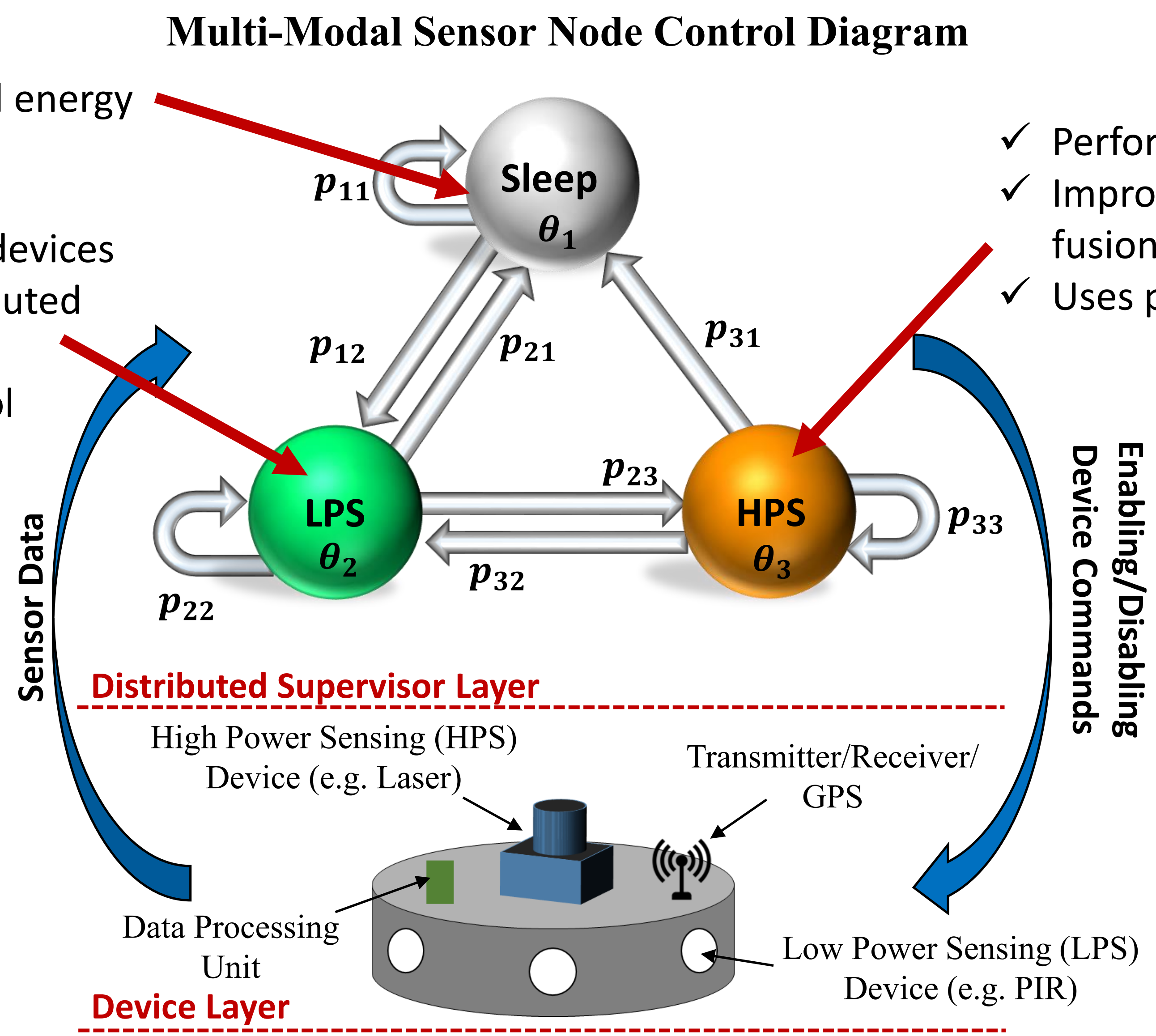
Sleep	LPS	HPS
$p_{31}^{s_i} = 0$	$p_{32}^{s_i} = 1 - P_{HPS}^{s_i}(k)$	$p_{33}^{s_i} = P_{HPS}^{s_i}(k)$

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

PFSA Overview

- ✓ 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



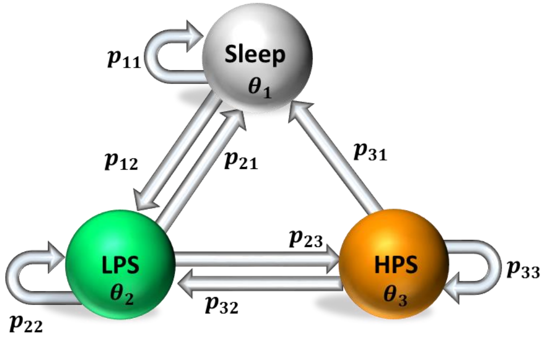
PIR: Passive Infrared Sensor

Results could be slightly different from the published POSE paper due to different sensing parameter choices.

POSE

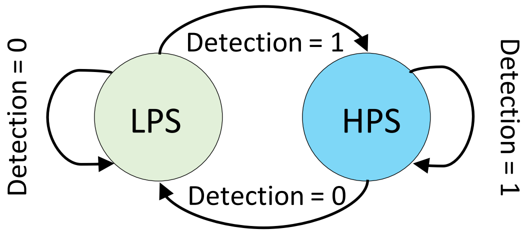
Missed Detection and Energy Characteristics

POSE



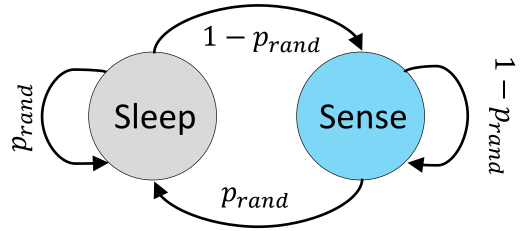
LPS-HPS Scheme

Distributed detection-based sensor activation

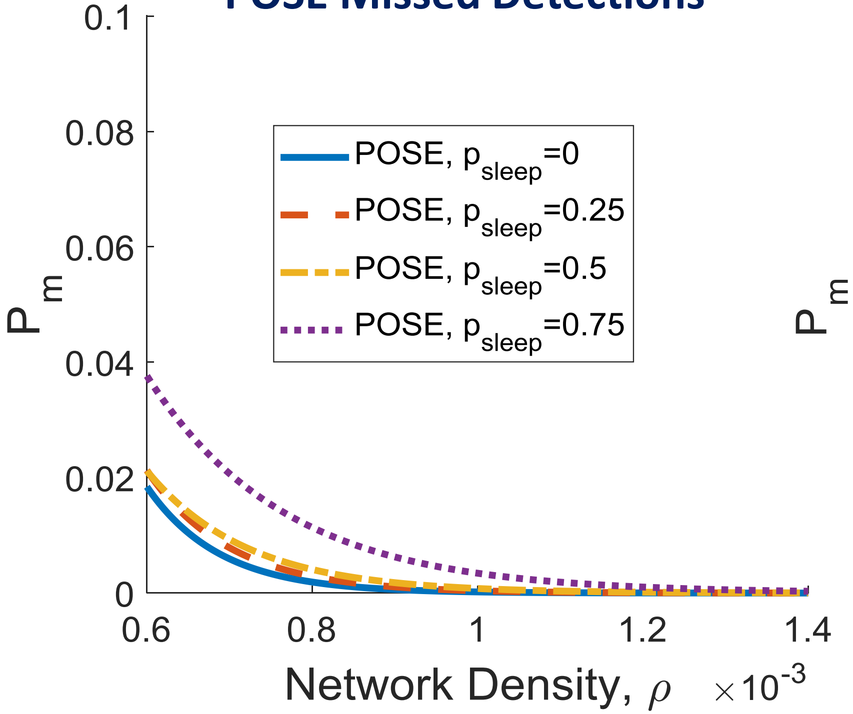


Random Scheduling Scheme

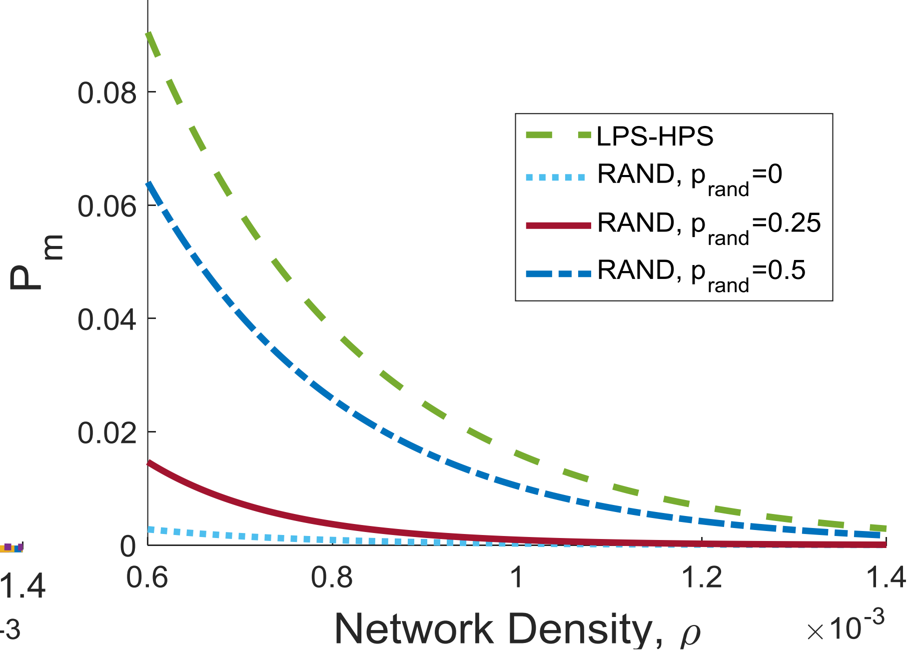
Distributed probabilistic sensor activation.



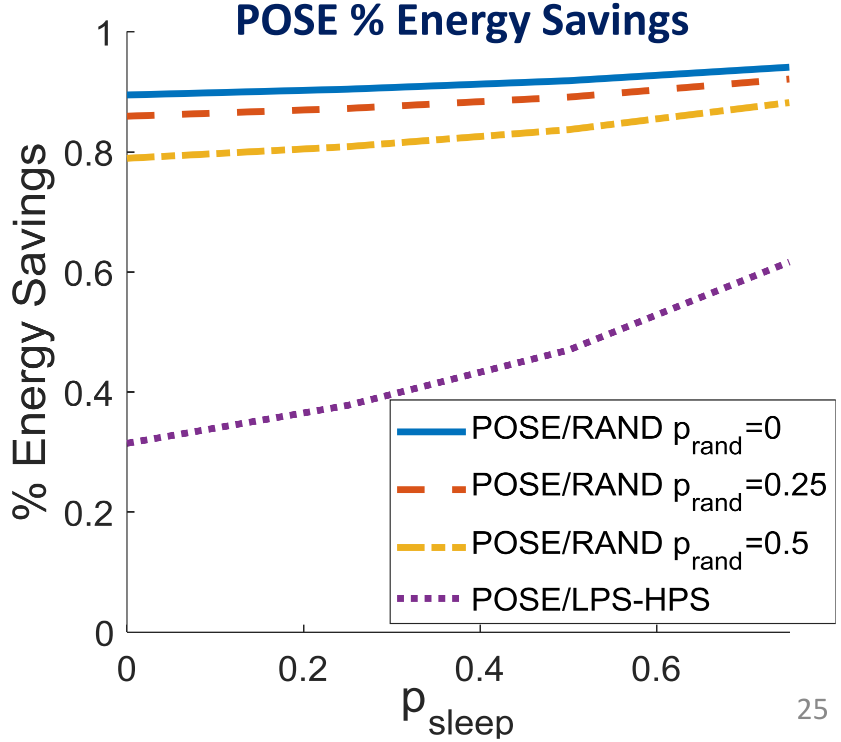
POSE Missed Detections



LPS-HPS and RAND Missed Detections

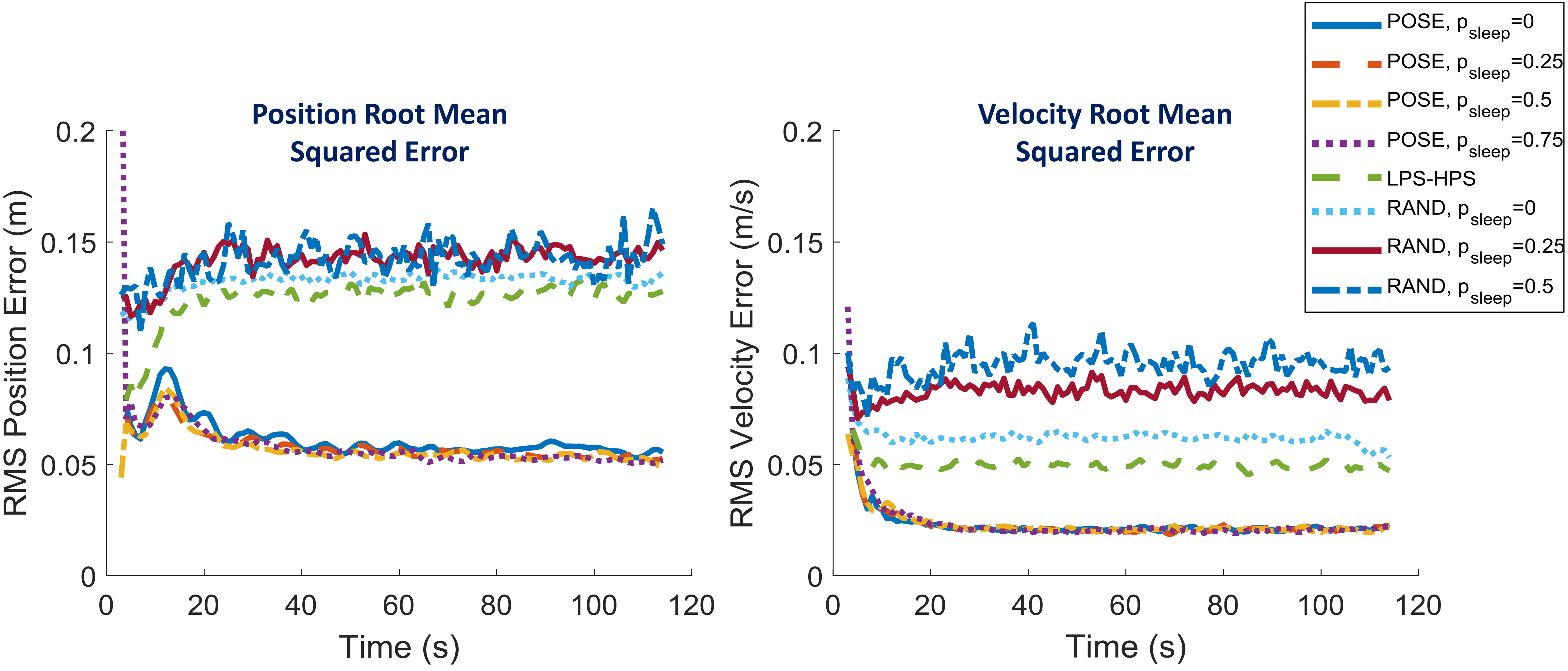


POSE % Energy Savings



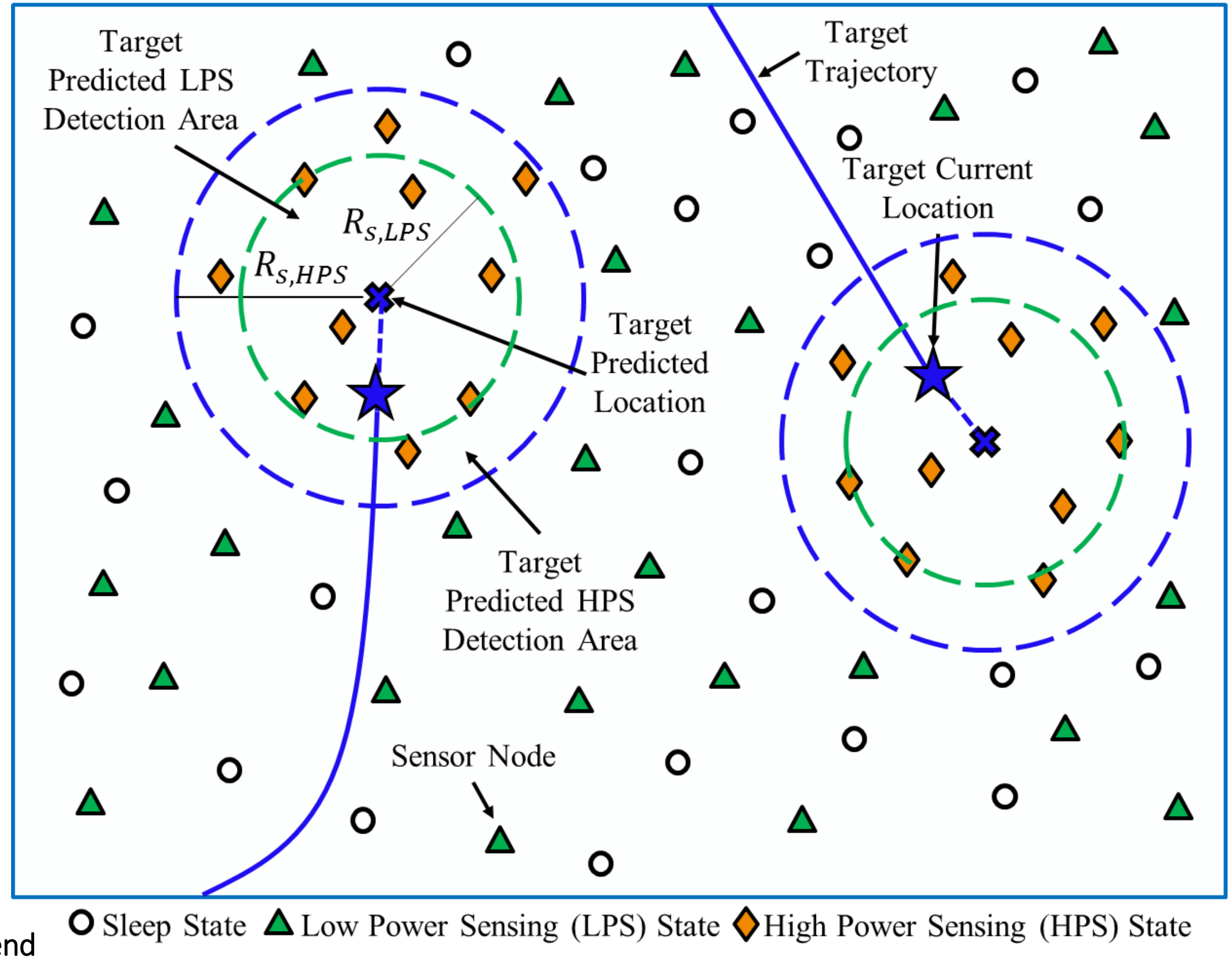
POSE

State Estimation Error Results



POSE

Conclusions and Limitations



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

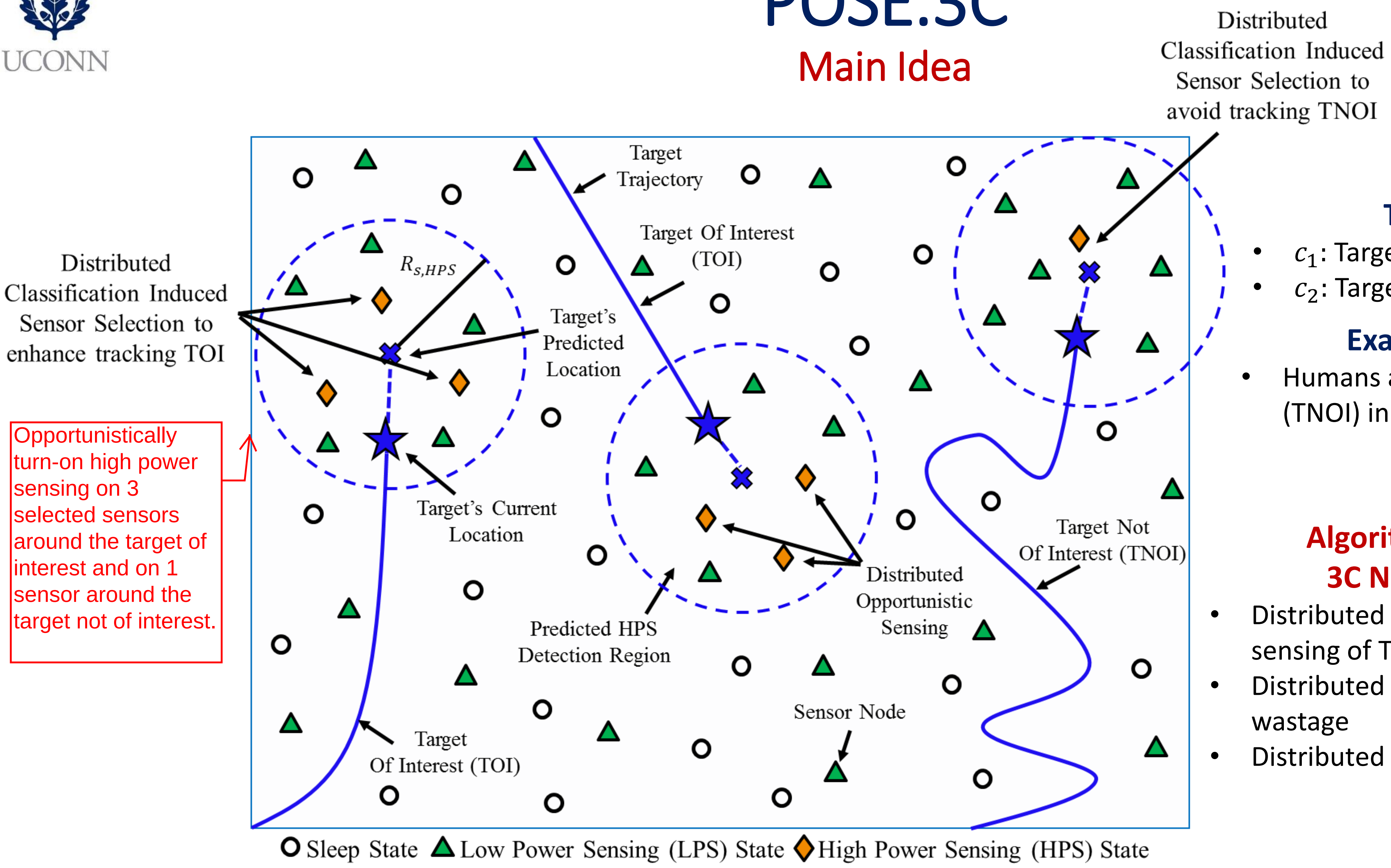
The POSE algorithm allows for
- Multi-modal sensor node control,
- Prediction-based Opportunistic Sensing,
- Low missed detection rates,
- Large energy savings, and
- Improved state estimation

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)

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 bo~~a~~rder surveillance

Algorithm Improvements: 3C Network Autonomy

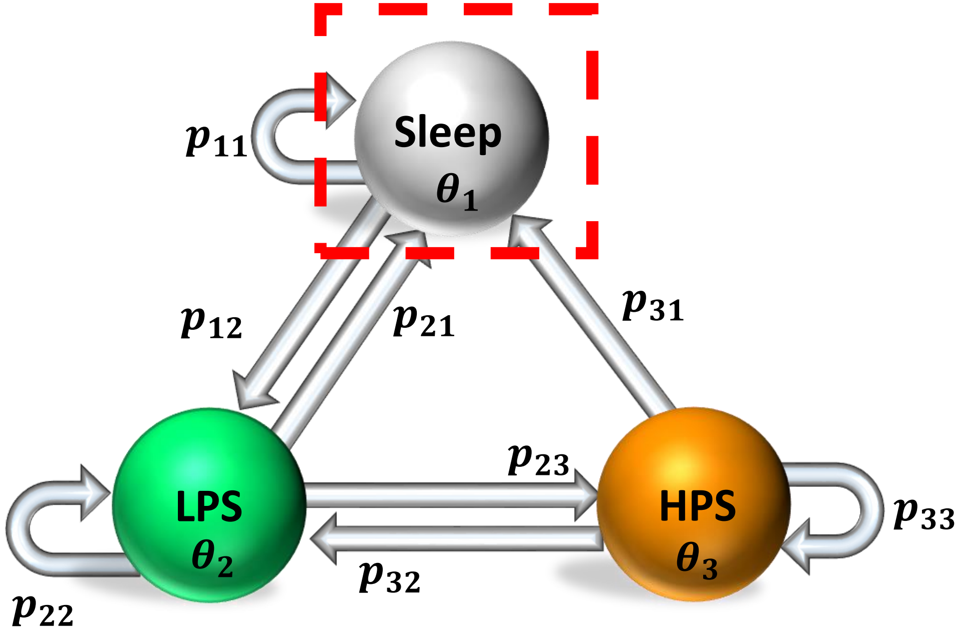
- Distributed Classification for opportunistic sensing of TOI
- Distributed Clustering to reduce energy wastage
- Distributed Control

Legend

- $R_{s,HPS}$: HPS Sensing Range

POSE.3C

Sleep State Algorithm



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

Sleep	LPS	HPS
$p_{11}^{s_i} = p_{sleep}$	$p_{12}^{s_i} = 1 - p_{sleep}$	$p_{13}^{s_i} = 0$

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

LPS: Low Power Sensing
HPS: High Power Sensing

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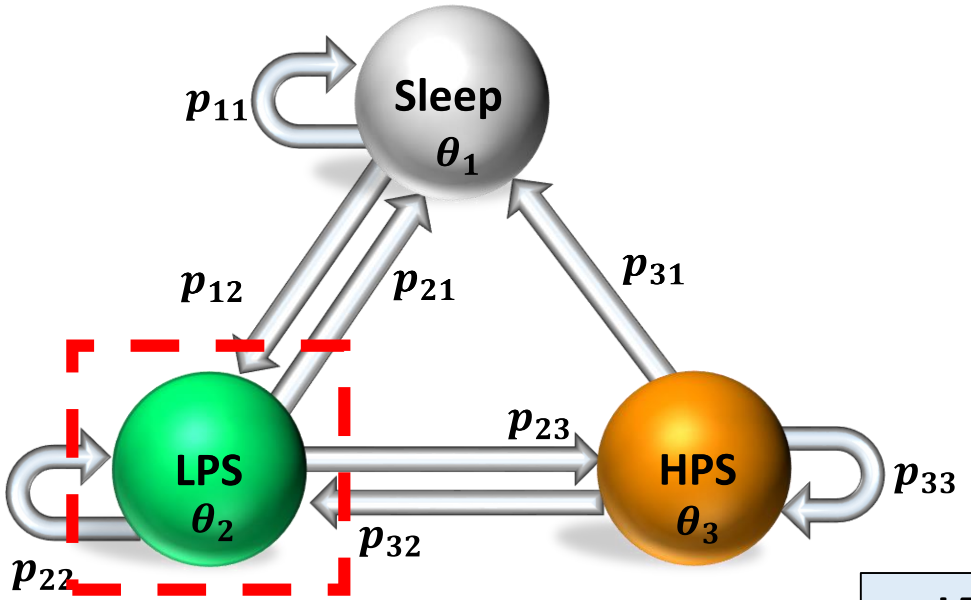
Low Power Sensing (LPS) State Algorithm



New Features

- Target class decision fusion
- Classification induced sensor selection

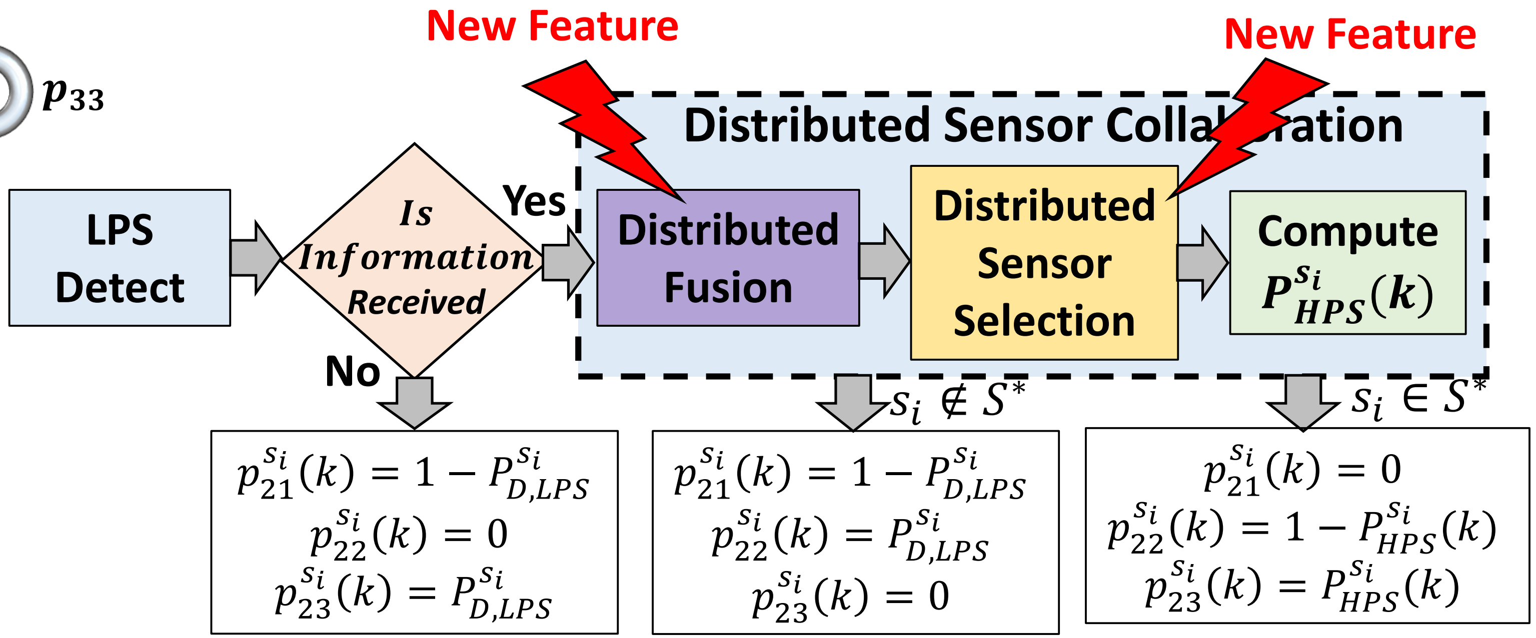
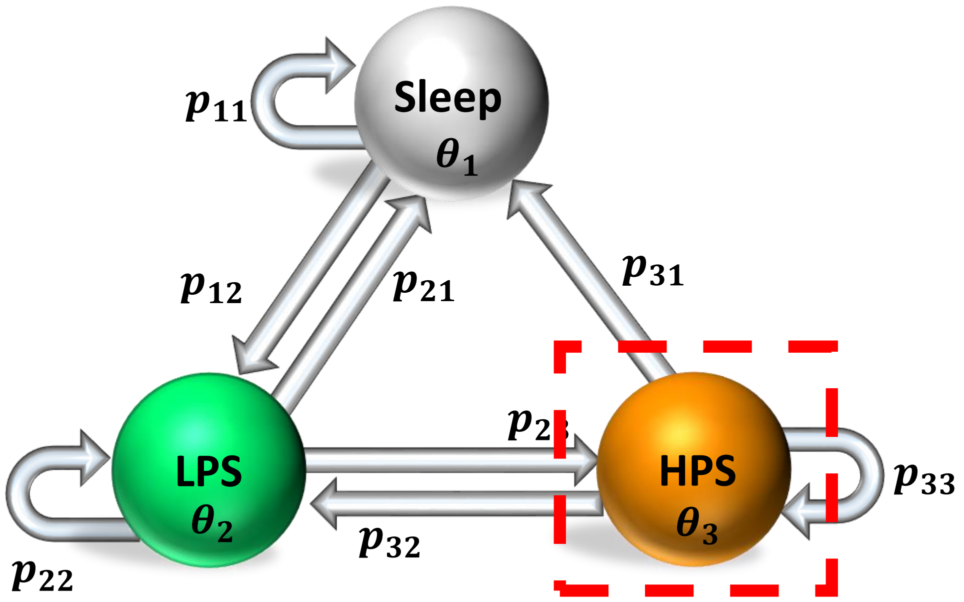


Figure: Low Power Sensing State Algorithm

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

POSE.3C

High Power Sensing (HPS) State Algorithm



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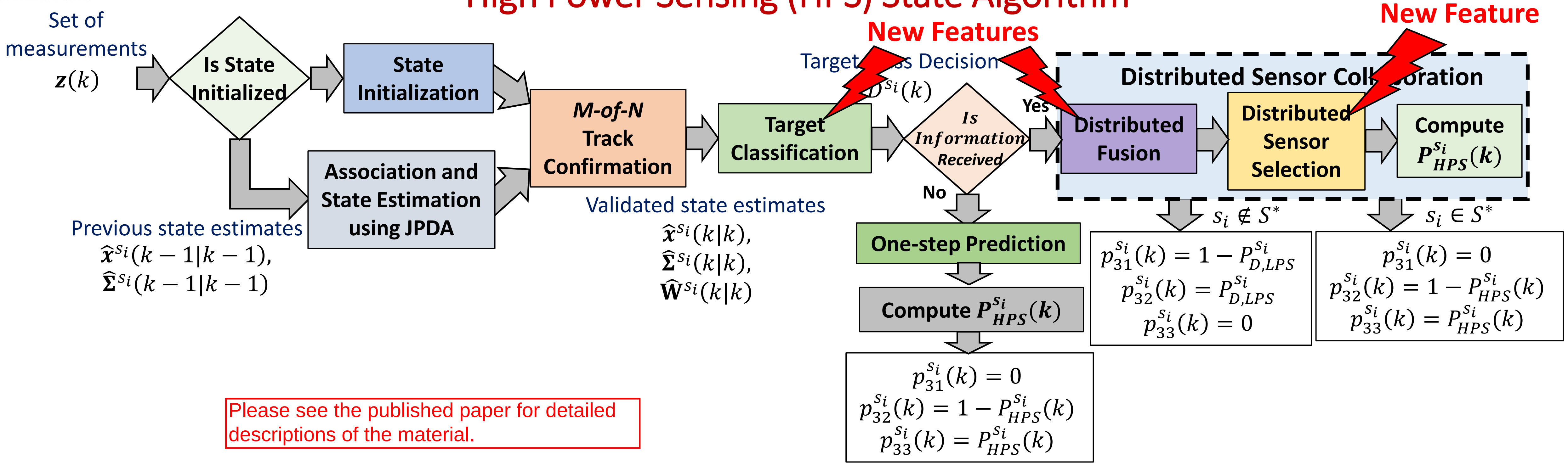
High Power Sensing (HPS) State Algorithm



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

Legend:

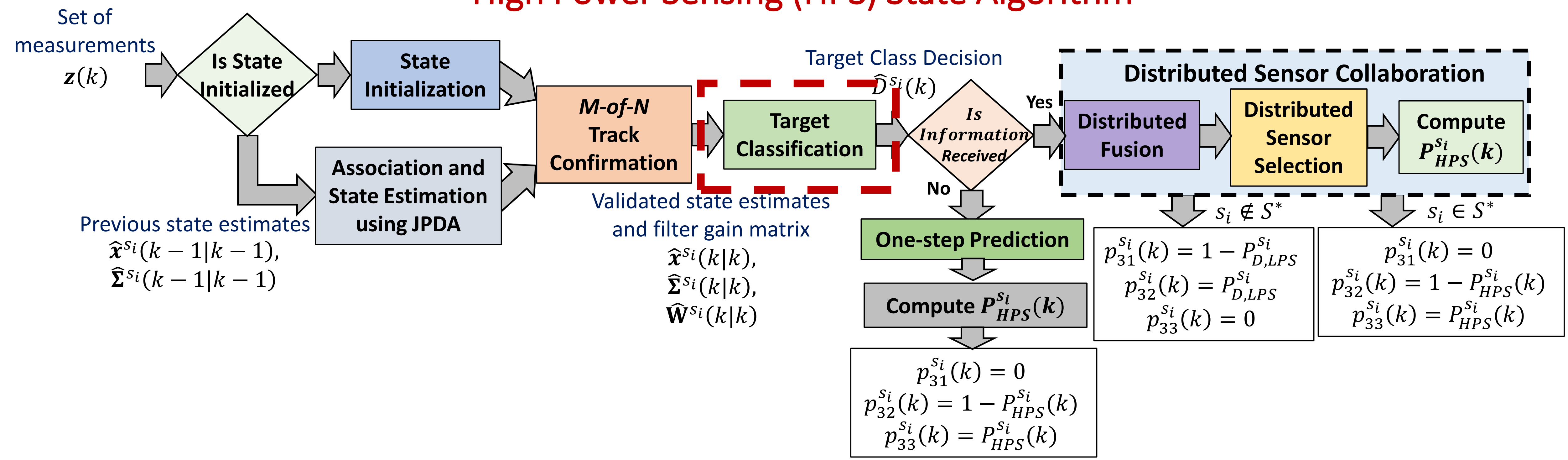
s_i: Sensor node i
$\hat{\mathbf{W}}^{s_i}(k|k)$: Filter gain matrix
$P_{HPS}^{s_i}(k)$: Probability that the target is located in HPS coverage area
$\mathbf{S}^*$: Set of selected sensors
$P_{D,LPS}^{s_i}$: LPS Probability of detection
$p_{xy}^{s_i}(k)$: State transition probability from state x to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

New Features

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

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

$\boldsymbol{S}^*$: 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

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High Power Sensing (HPS) State Algorithm

Classify the type of target being tracked

Advantages:

- Reduces energy wastage

Validated state estimates: $\hat{\boldsymbol{x}}^{s_j}(k|k), \hat{\boldsymbol{\Sigma}}^{s_j}(k|k), \widehat{\boldsymbol{W}}^{s_j}(k)$ → **Target Classification**

→ *Target Class Decision:* $\widehat{\boldsymbol{D}}^{s_i}(k)$

→ *Validated state estimates*: $\hat{\boldsymbol{x}}^{s_j}(k|k), \hat{\boldsymbol{\Sigma}}^{s_j}(k|k), \widehat{\boldsymbol{W}}^{s_j}(k)$

Target Class Definition:

$\boldsymbol{c_1}$: Target of Interest (TOI)

$\boldsymbol{c_2}$: Target Not Of Interest (TNOI)

Classifier performance is modeled by a Confusion Matrix

		Estimated Class	
		TOI	TNOI
True Class	TOI	**A**	**B**
	TNOI	**C**	**D**

Confusion Matrix

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

Maps to a Decision

$$\hat{D}^{s_i}(k) \in \{0,1\}$$

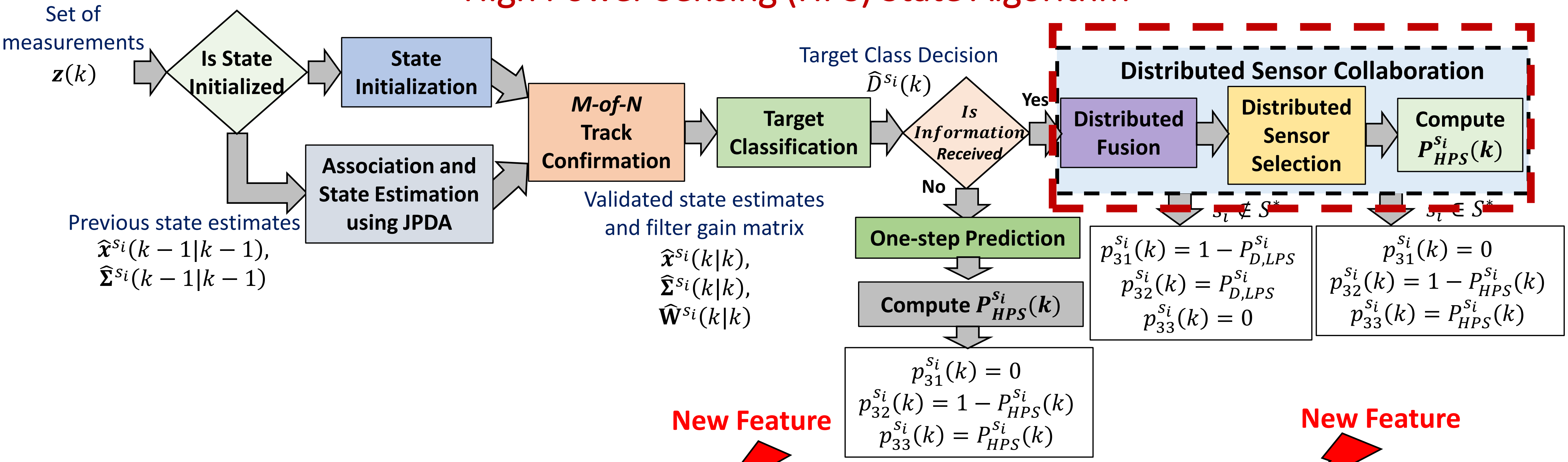
Where:

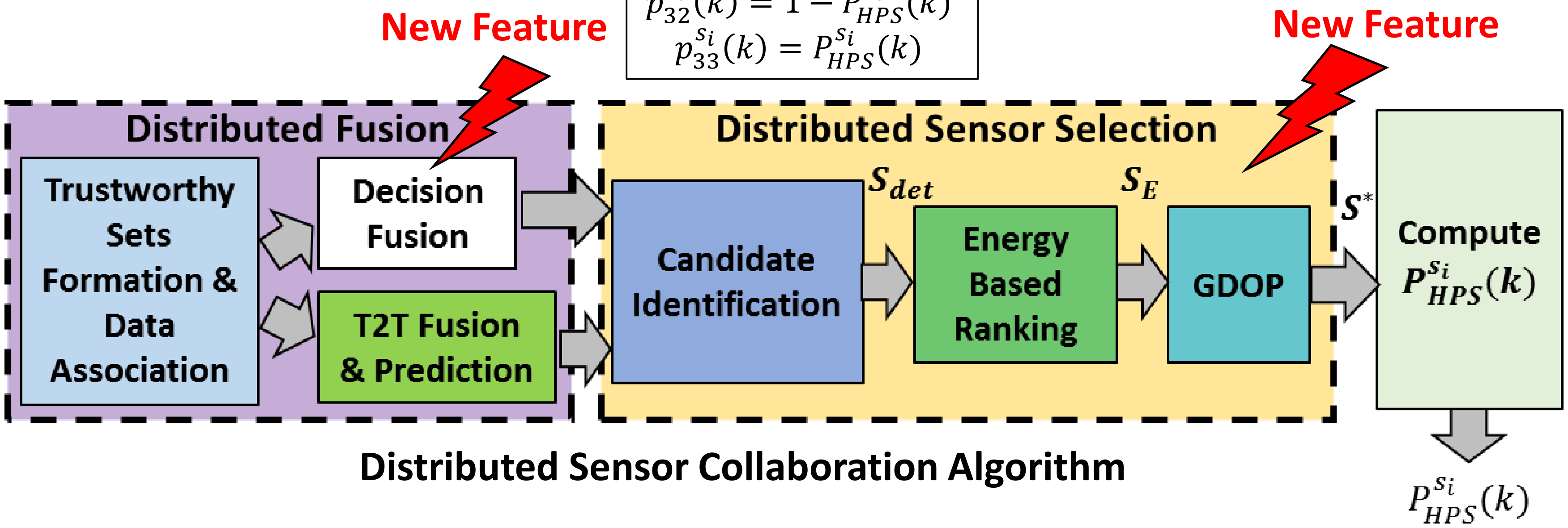
$\hat{D}^{s_i}(k) = 1$: TOI

$\hat{D}^{s_i}(k) = 0$: TNOI

POSE.3C

High Power Sensing (HPS) State Algorithm





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 candidate sensors

S_E: Set of candidates with highest energy remaining

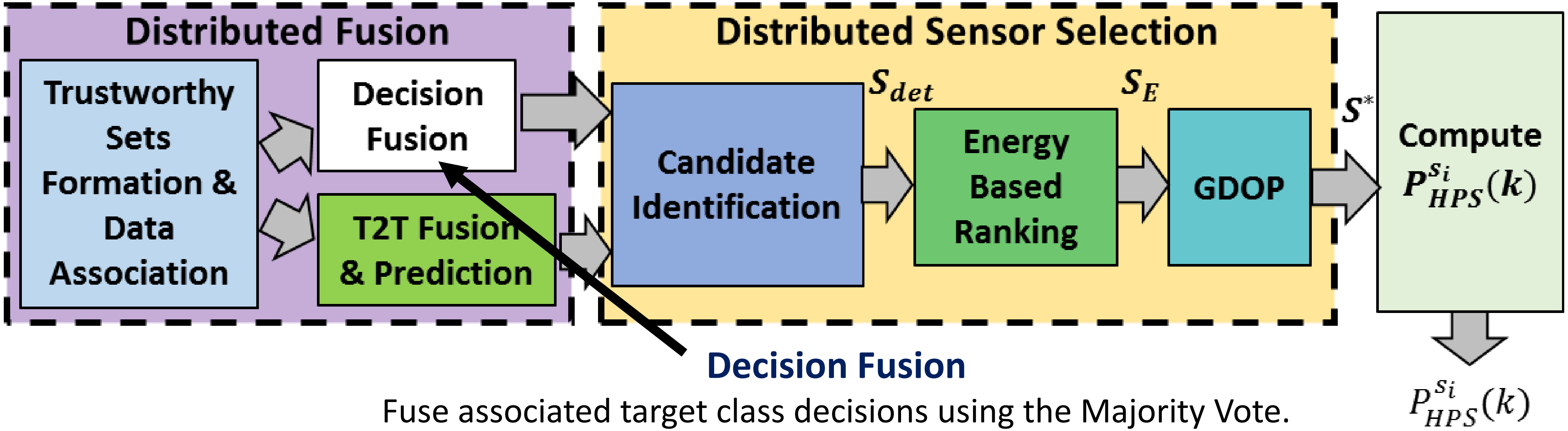
S^*: Set of selected sensors

$P_{D,LPS}^{s_i}$: LPS Probability of detection

$p_{xy}^{s_i}(k)$: State transition probability from state x to state y

POSE.3C

Distributed Sensor Collaboration Algorithm



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

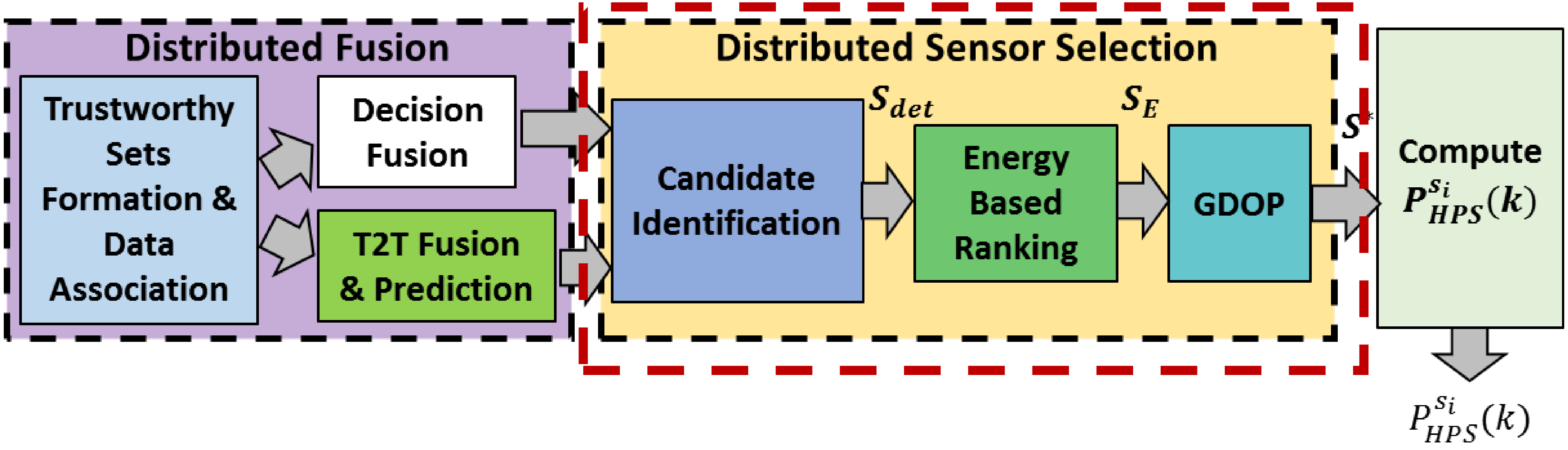
$$\hat{D}^{s_i,c}(k) = \begin{cases} 1 & if \ \dfrac{1}{\left|\hat{\boldsymbol{I}}_T^{s_i,c}(k)\right|} \displaystyle\sum_{s_j \in \mathcal{N}_T^{s_i,c}} \hat{D}^{s_j}(k) \geq 0.5 \\ 0 & else \end{cases}$$

Where $\hat{\boldsymbol{I}}_T^{s_i,c}(k) = \left\{\left(\hat{\boldsymbol{x}}^{s_j}, \hat{\boldsymbol{\Sigma}}^{s_j}, \widehat{\boldsymbol{W}}^{s_j}, \hat{D}^{s_j}(k)\right), \forall s_j \in \mathcal{N}_T^{s_i,c}\right\} \subseteq \hat{\boldsymbol{I}}_T^{s_i}(k)$ is the set of associated trustworthy information

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

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

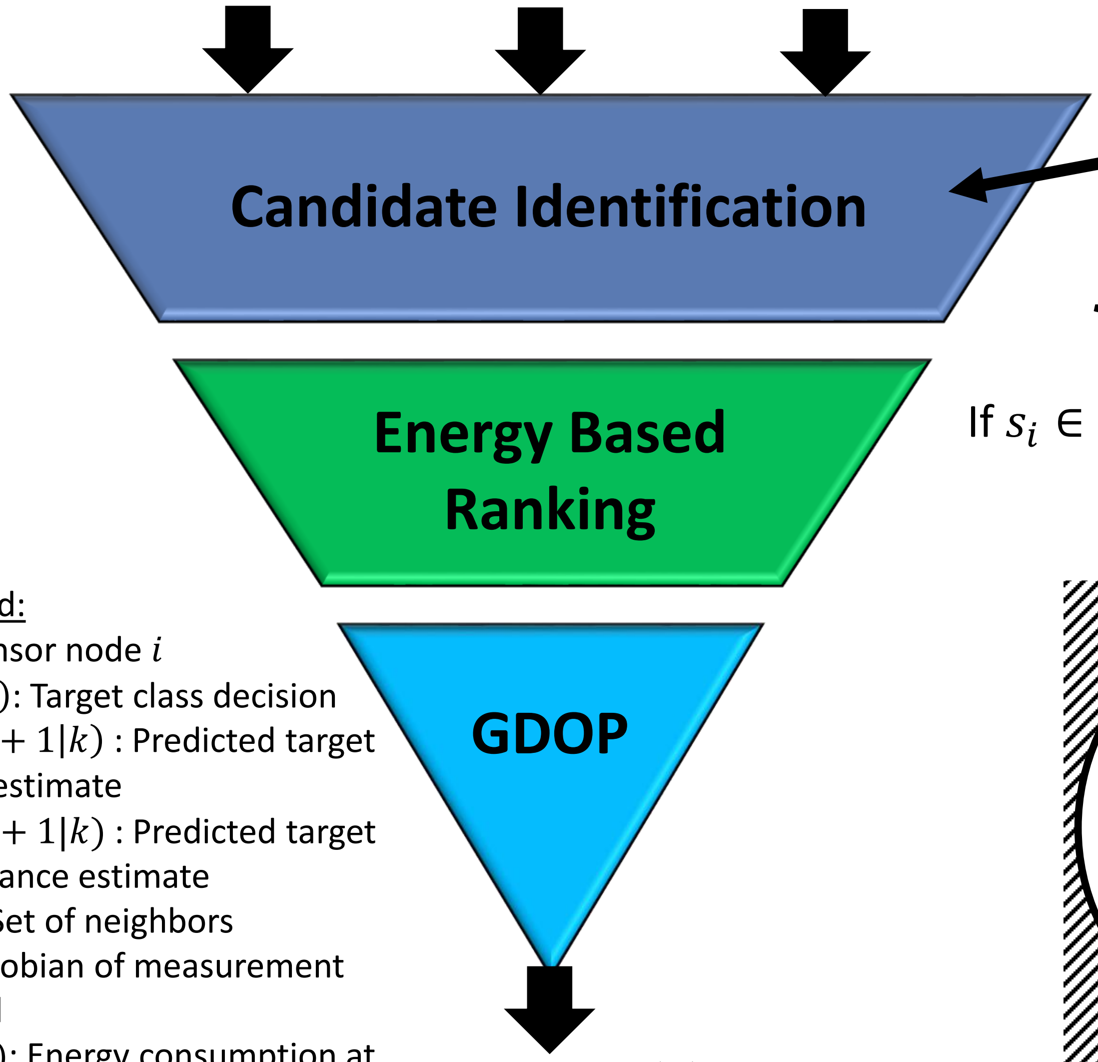
S_E: Set of sensors with the highest energy remaining

S^*: Set of selected sensors

POSE.3C

Distributed Sensor Selection Algorithm

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



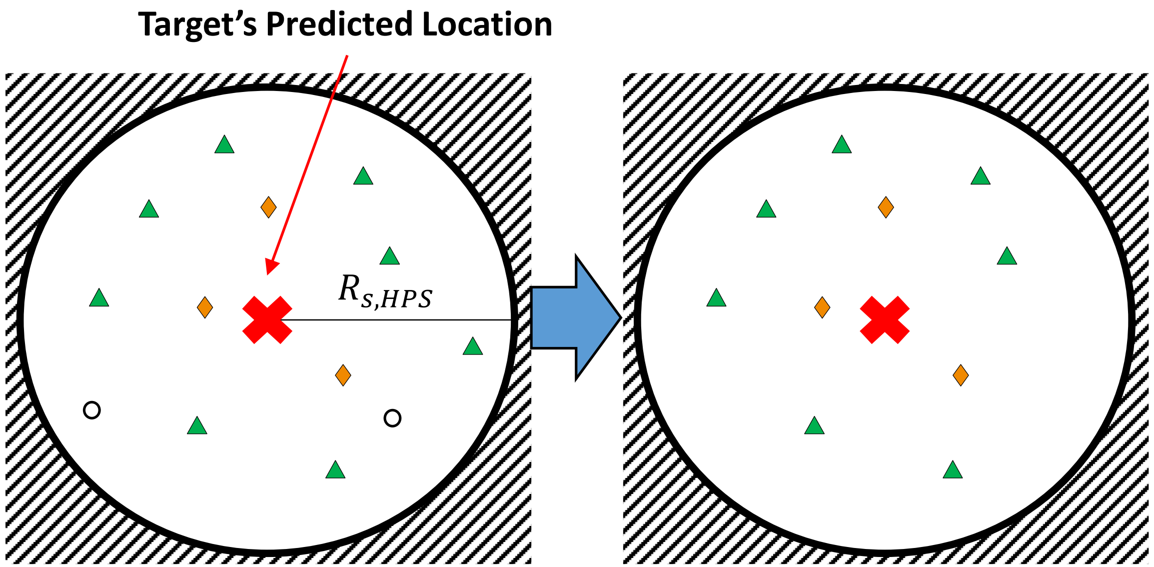
$$\boldsymbol{S}^* = \max_{\widetilde{\boldsymbol{S}}} \mu(\widetilde{\boldsymbol{S}})$$

Candidate Identification

Identify the set of sensors that can detect the predicted target location

$$\boldsymbol{S_{det}} = \left\{ s_j \in (\mathcal{N}^{s_i} \cup s_i);\ \left|\left|\boldsymbol{u}^{s_j} - \boldsymbol{H}\hat{\boldsymbol{x}}^{s_i}(k+1|k)\right|\right| \le R_{s,HPS} \right\}$$

If $s_i \in \boldsymbol{S_{det}}$, s_i will broadcast it's energy consumed $E_c^{s_i}(k) = \sum_{\kappa=0}^{k} E^{s_i}(\kappa)$

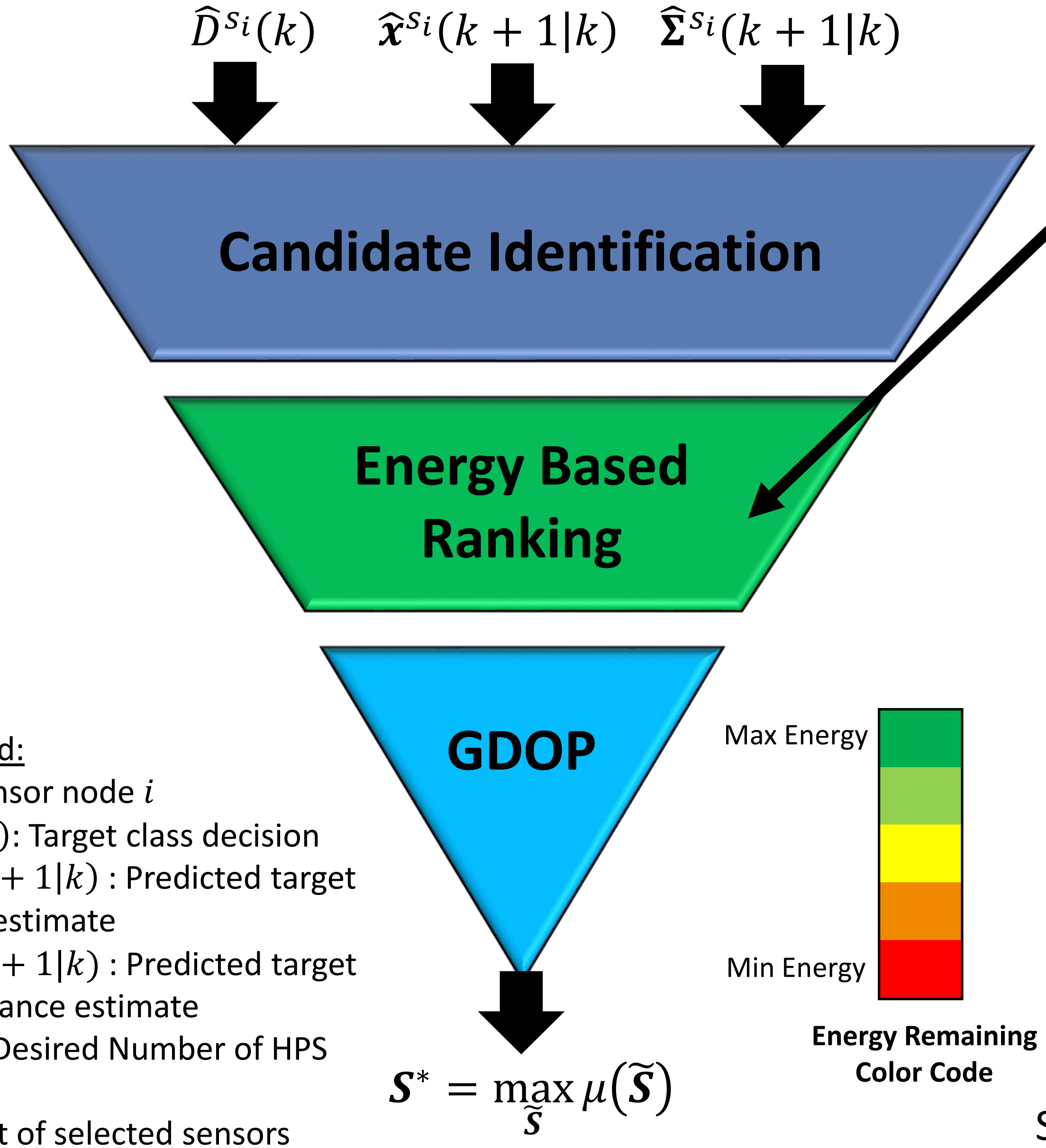


Candidate Region Set of Candidate Sensors, $\boldsymbol{S}_{det}$

Legend:
s_i: Sensor node i
$\widehat{D}^{s_i}(k)$: Target class decision
$\hat{\boldsymbol{x}}^{s_i}(k+1|k)$: Predicted target state estimate
$\widehat{\boldsymbol{\Sigma}}^{s_i}(k+1|k)$: Predicted target covariance estimate
$\mathcal{N}^{s_i}$: Set of neighbors
$\boldsymbol{H}$: Jacobian of measurement model
$E^{s_i}(k)$: Energy consumption at time k
$\boldsymbol{S}^*$: Set of selected sensors

POSE.3C

Distributed Sensor Selection Algorithm



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

Energy Remaining Color Code

Energy Based Ranking

Identify the set of sensors with the most energy remaining

1. Rank the sensors in $\boldsymbol{S}_{det}$ by their energy remaining, $E_R^{s_j}(k)$

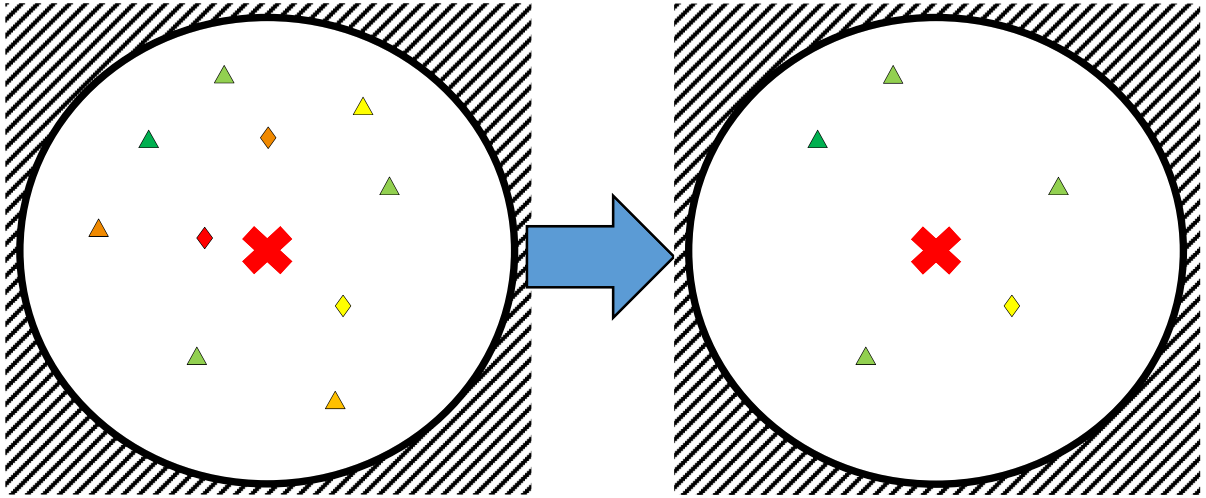
$$E_R^{s_j}(k) = 1 - \frac{E_c^{s_j}(k) + E_{HPS}}{E_0}$$

- $E_c^{s_j}(k)$: 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 $\boldsymbol{S}_{\boldsymbol{E}}$.

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

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

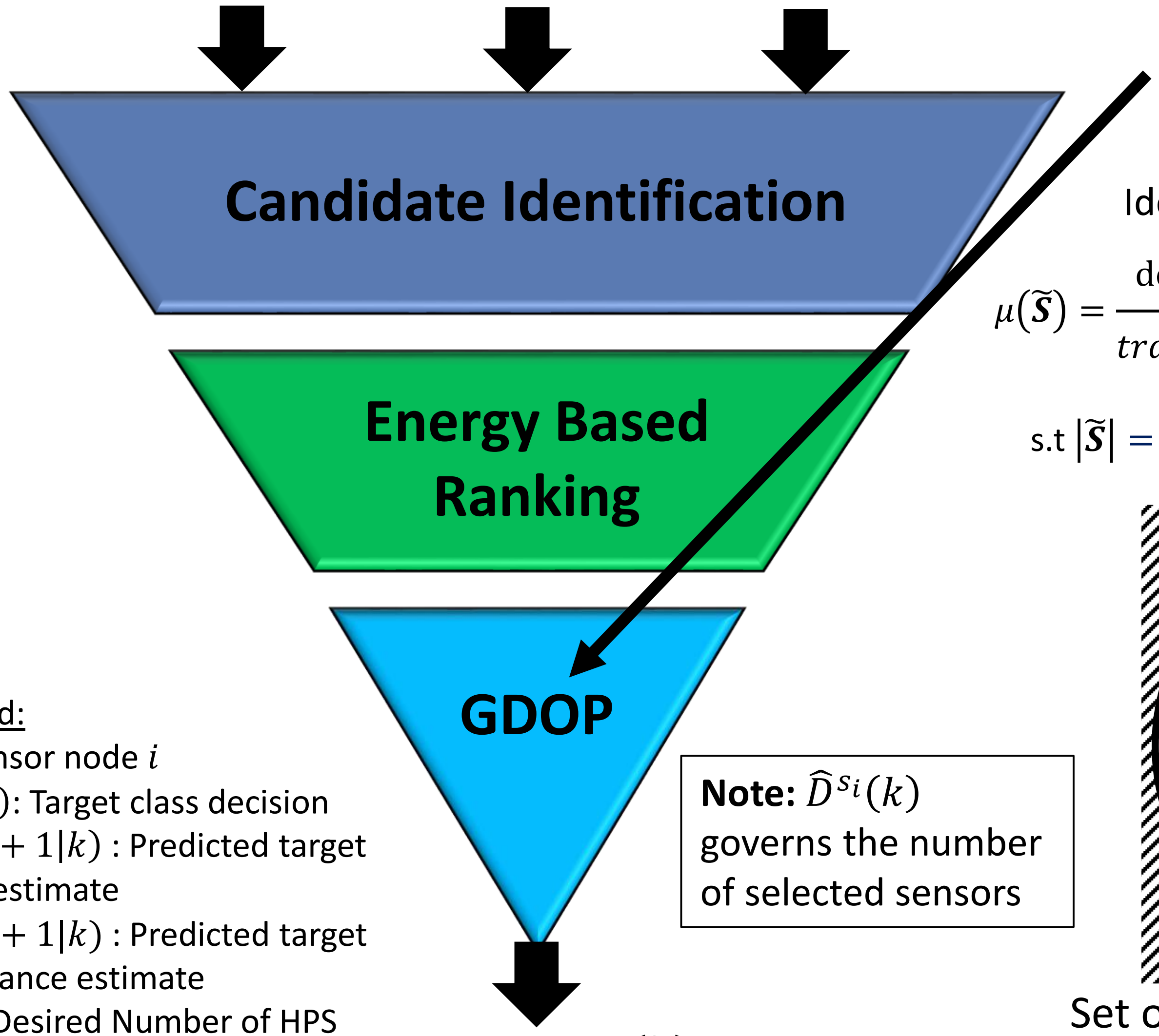


Set of Candidate Sensors, $\boldsymbol{S}_{det}$ Set of Energy Ranked Sensors, $\boldsymbol{S}_{\boldsymbol{E}}$

POSE.3C

Distributed Sensor Selection Algorithm

$\widehat{D}^{s_i}(k)$ $\quad \widehat{\boldsymbol{x}}^{s_i}(k+1|k)$ $\quad \widehat{\boldsymbol{\Sigma}}^{s_i}(k+1|k)$



$$\boldsymbol{S}^* = \max_{\widetilde{\boldsymbol{S}}} \mu(\widetilde{\boldsymbol{S}})$$

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

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

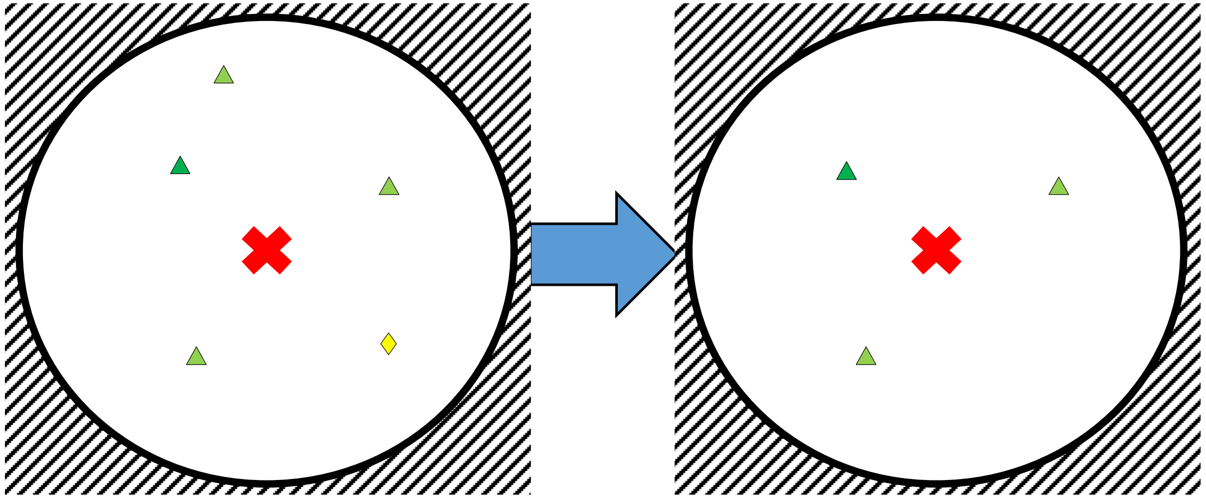
Geometrical Dilution Of Precision (GDOP)

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

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

$$\mu(\widetilde{\boldsymbol{S}}) = \frac{\det\left(\boldsymbol{J}(\widetilde{\boldsymbol{S}})\right)}{trace\left(\boldsymbol{J}(\widetilde{\boldsymbol{S}})\right)}, \qquad \boldsymbol{J}(\widetilde{\boldsymbol{S}}) = \sum_{s_j \in \widetilde{\boldsymbol{S}}} \frac{1}{\sigma_\phi^2 r_{s_j}^2} \begin{bmatrix} \sin\left(\phi_{s_j}\right)^2 & -\sin\left(\phi_{s_j}\right)\cos\left(\phi_{s_j}\right) \\ -\sin\left(\phi_{s_j}\right)\cos\left(\phi_{s_j}\right) & \cos\left(\phi_{s_j}\right)^2 \end{bmatrix}$$

s.t $|\widetilde{\boldsymbol{S}}| = N_{sel} = \begin{cases} N_{sel} & if\ \widehat{D}^{s_i}(k) = 1 \\ 1 & else \end{cases}$: The desired number of HPS sensors.



Set of Energy Ranked Sensors, $\boldsymbol{S_E}$ $\qquad$ Set of Selected Sensors, $\boldsymbol{S}^*$

[1] L. M. Kaplan, “Local node selection for localization in a distributed sensor network,” *IEEE Transactions on Aerospace and Electronic Systems*, vol. 42, no. 1, pp. 136–146, 2006.

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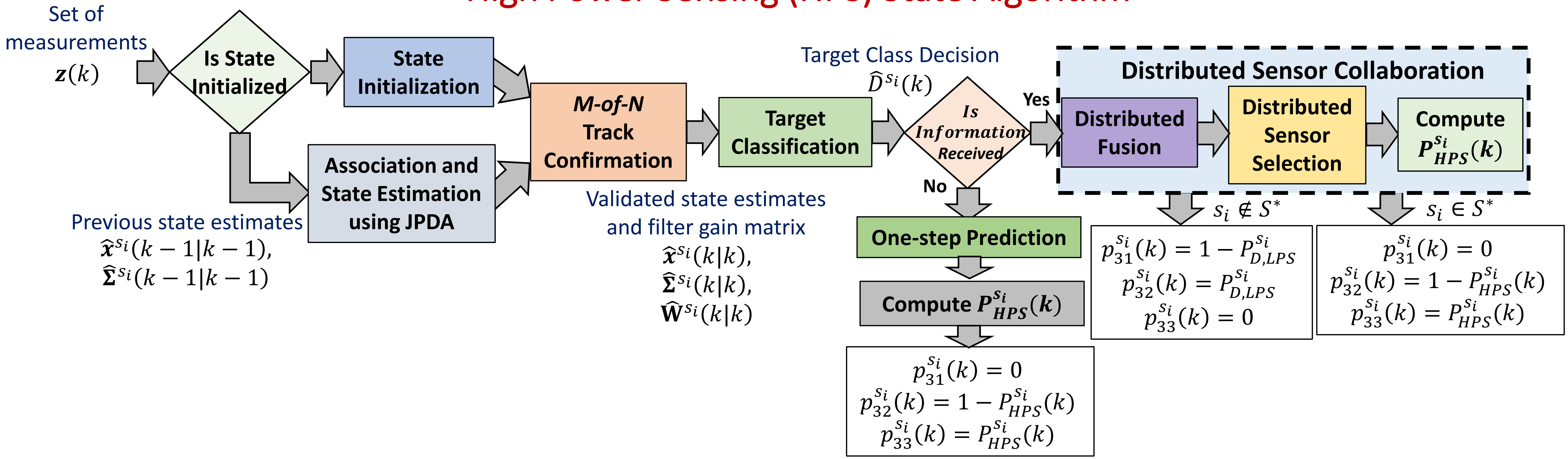
High Power Sensing (HPS) State Algorithm



<u>Legend:</u>

s_i: Sensor node i

$P_{HPS}^{s_i}(k)$: Probability that the target is located in HPS coverage area

$\boldsymbol{S}^*$: Set of selected sensors

$P_{D,LPS}^{s_i}$: LPS Probability of detection

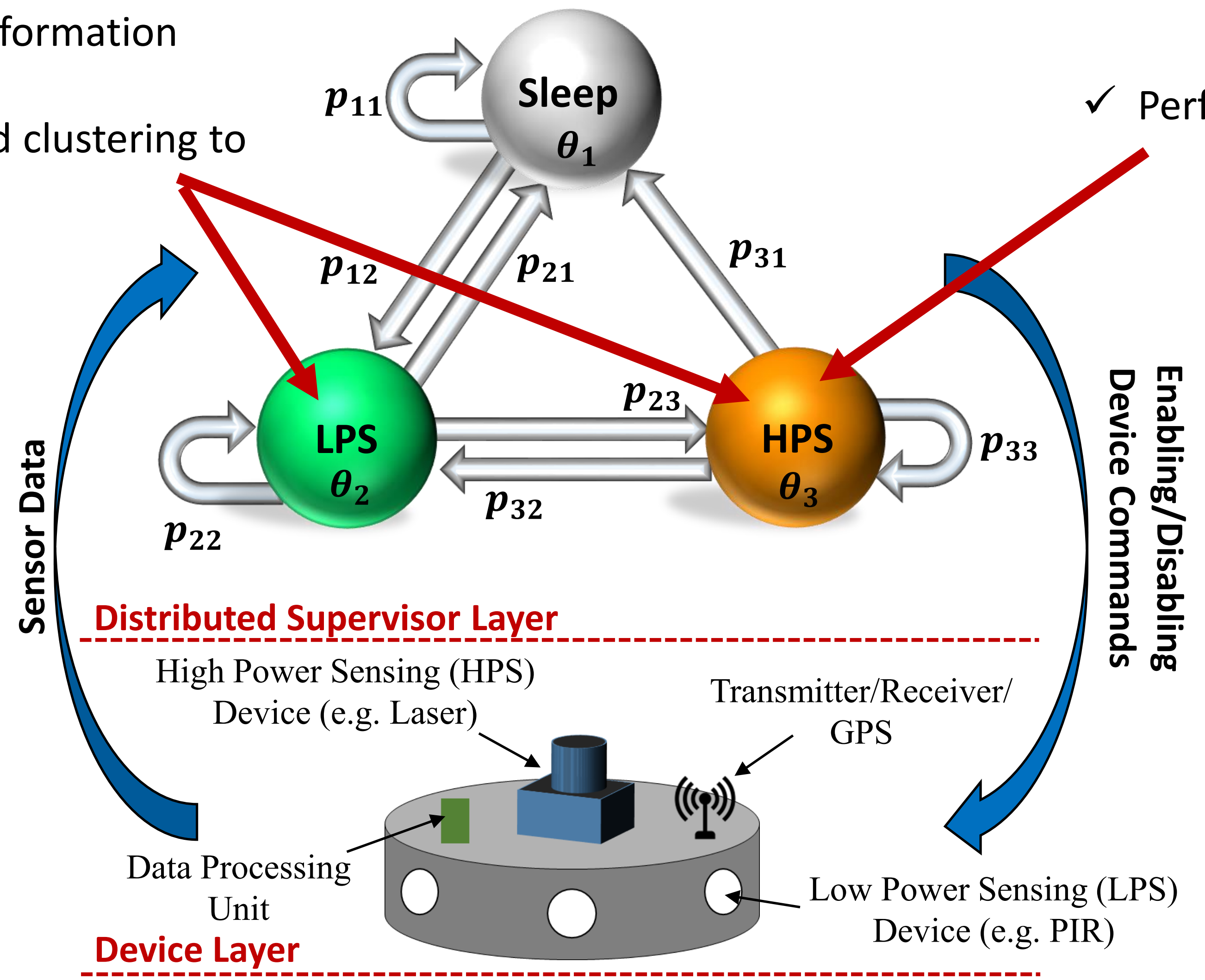
$p_{xy}^{s_i}(k)$: State transition probability from state x to state y

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



PIR: Passive Infrared Sensor

POSE.3C

Expected Energy Consumption Characteristics

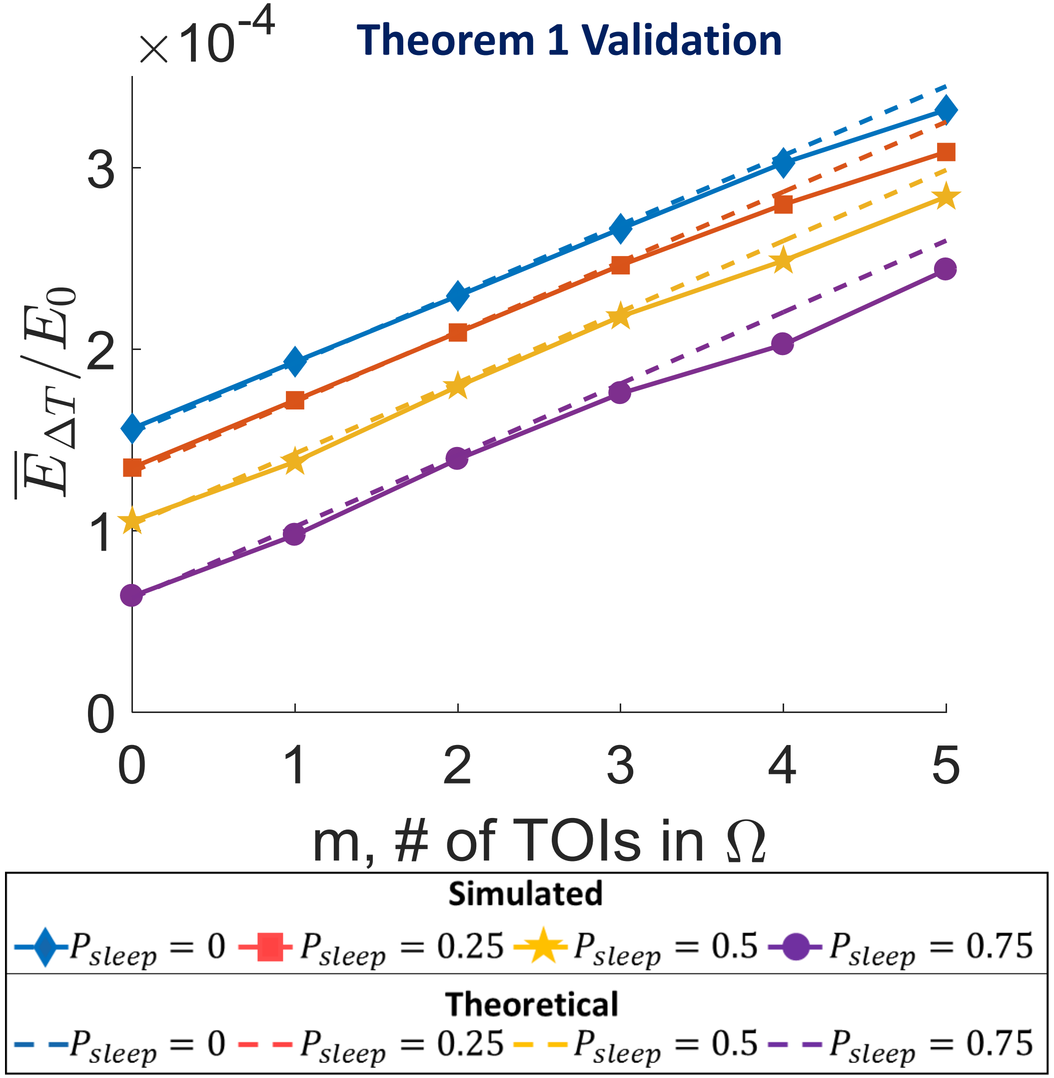
Theorem 1: The expected energy consumption of the POSE.3C network during a ΔT time interval is given as

$$\boxed{\bar{E}_{\Delta T}(m) = N_{sel} m \bar{E}^{\Omega_1^*} + \left(\rho A_{\Omega_1} - N_{sel} m\right)\bar{E}^{\Omega_1^{*\prime}} + \rho A_{\Omega_2}\bar{E}^{\Omega_2} + \rho A_{\Omega_3}\bar{E}^{\Omega_3}}$$

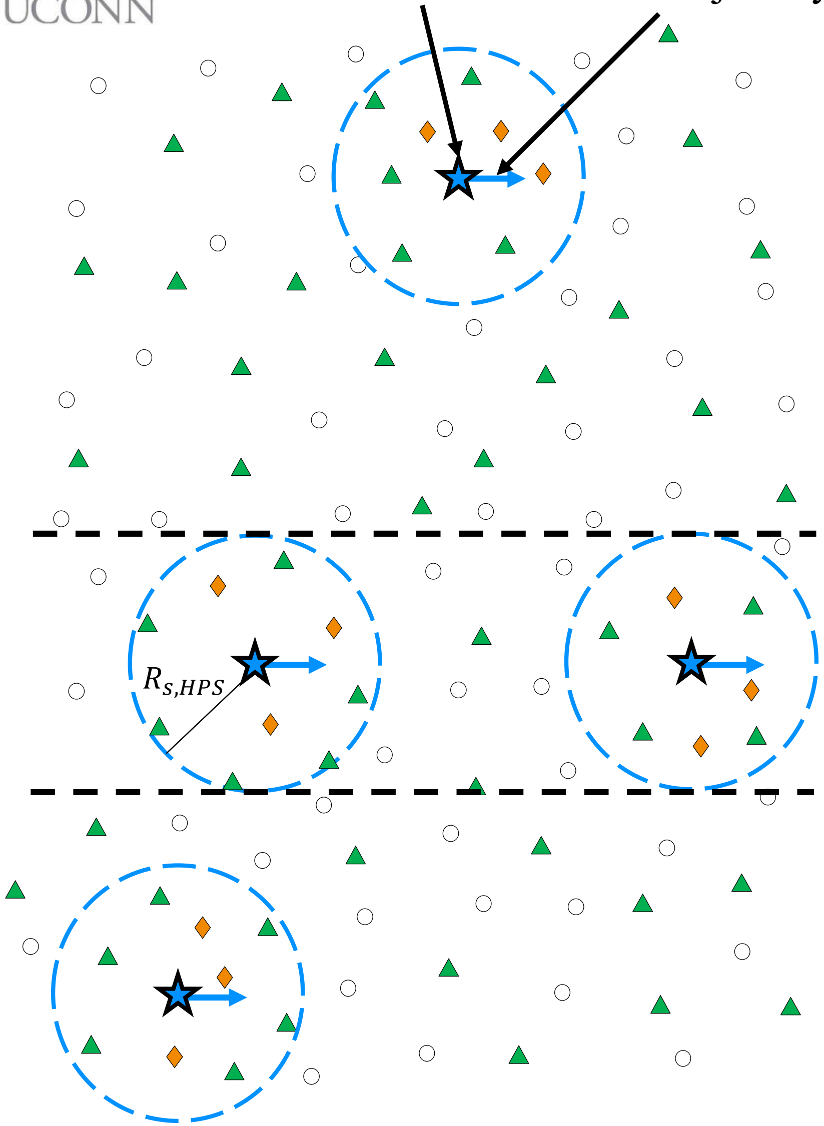
- ρ: Network Density
- $\bar{E}^{\Omega_1^*} = E_{LPS}^{\Omega_1} p_2^{\Omega_1^*} + E_{HPS}^{\Omega_1} p_3^{\Omega_1^*}$: Expected energy consumption in Ω_1^*
- $\bar{E}^{\Omega_1^{*\prime}} = E_{Sleep} p_1^{\Omega_1^{*\prime}} + E_{LPS}^{\Omega_1} p_2^{\Omega_1^{*\prime}}$: Expected energy consumption in $\Omega_1^{*\prime}$
- $\bar{E}^{\Omega_2} = E_{Sleep} p_1^{\Omega_2} + E_{LPS}^{\Omega_2} p_2^{\Omega_2}$: Expected energy consumption in Ω_2
- $\bar{E}^{\Omega_3} = E_{Sleep} p_1^{\Omega_3} + E_{LPS}^{\Omega_3} p_2^{\Omega_3} + E_{HPS}^{\Omega_3} p_3^{\Omega_3}$: Expected energy consumption in Ω_3
- Steady-state probabilities of a node being in each state within each region:

$$\begin{bmatrix} p_1 \\ p_2 \\ p_3 \end{bmatrix}^{\Omega_1^*} = \begin{bmatrix} 0 \\ 1-\alpha \\ \alpha \end{bmatrix}, \qquad \begin{bmatrix} p_1 \\ p_2 \\ p_3 \end{bmatrix}^{\Omega_1^{*\prime}} = \begin{bmatrix} \dfrac{1-\alpha}{2-p_{sleep}-\alpha} \\ \dfrac{1-p_{sleep}}{2-p_{sleep}-\alpha} \\ 0 \end{bmatrix},$$

$$\begin{bmatrix} p_1 \\ p_2 \\ p_3 \end{bmatrix}^{\Omega_2} = \begin{bmatrix} \dfrac{1-p_{fa}}{2-p_{sleep}-p_{fa}} \\ \dfrac{1-p_{sleep}}{2-p_{sleep}-p_{fa}} \\ 0 \end{bmatrix}, \qquad \begin{bmatrix} p_1 \\ p_2 \\ p_3 \end{bmatrix}^{\Omega_3} = \begin{bmatrix} \dfrac{1-2p_{fa}}{2-p_{sleep}-2p_{fa}} \\ \dfrac{(1-p_{fa})(1-p_{sleep})}{2-p_{sleep}-2p_{fa}} \\ \dfrac{2p_{fa}(1-p_{sleep})}{2-p_{sleep}-2p_{fa}} \end{bmatrix}$$



POSE.3C



○ Sleep State ▲ Low Power Sensing (LPS) State
◆ High Power Sensing (HPS) State

Figure: POSE.3C Network

Network Lifetime Definition

Consider:

- Multiple targets travel through the network along similar paths
- A path Ω_γ contains the highest frequency of target's traveling through it
- The number of targets located in Ω_γ during each time step is λ

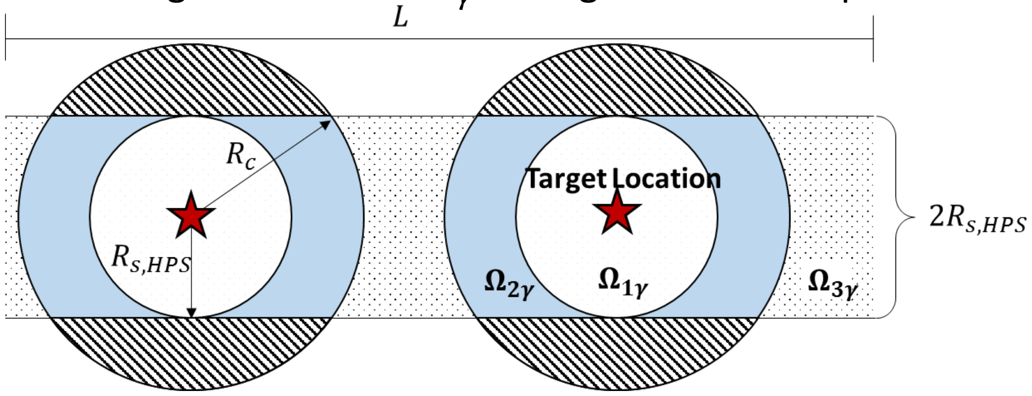


Figure: Visual Representation of Ω_γ with $\lambda = 2$ targets

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

$$\frac{\sum_{s_j \in S_\gamma} \left(E_0^{s_j} - E_c^{s_j}(\bar{T}_{Life}) \right)}{\sum_{s_j \in S_\gamma} E_0^{s_j}} = \eta$$

Legend:

L: Length of the tube Ω_γ
R_c: Communication Radius
$R_{s,HPS}$: HPS Sensing Range
S_j: Set of sensor nodes in Ω_γ
$E_0^{s_j}$: Initial energy of node s_j
$E_c^{s_j}$: Energy consumed by node s_j
$\Omega_{1\gamma}$: 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

POSE.3C

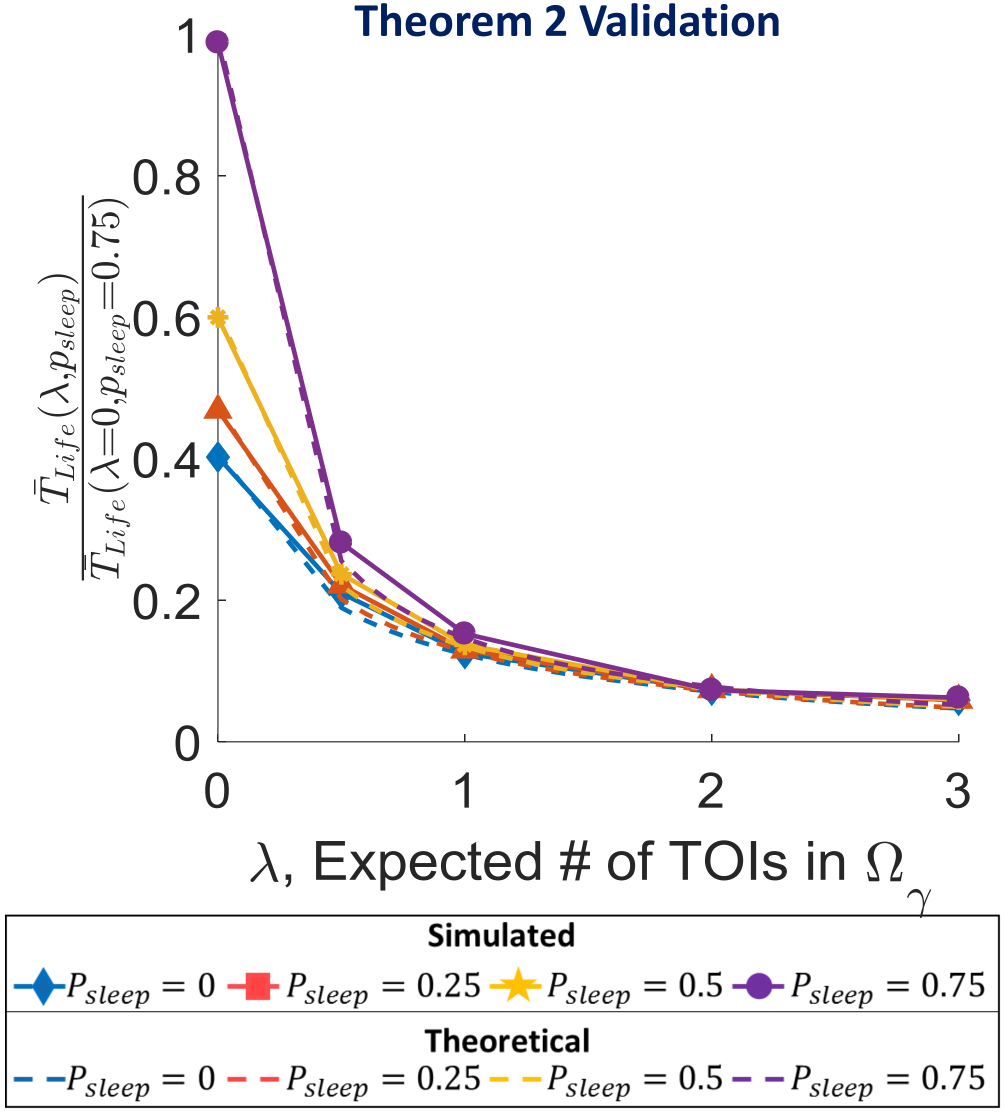
Network Lifetime Characteristics

Theorem 2: The expected lifetime of the POSE.3C network is

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

ρ: Network Density
$R_{s,HPS}$: HPS device sensing radius
L: Length of the target track
E_0: Initial sensor energy
η: Minimum percent of energy tolerated before Ω_γ is considered dead
L: Length of the target track
λ: Expected number of TOI in Ω_γ
Ω_γ: 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 ΔT time interval

Theorem 2 Validation



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:

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

b) For a mature target:

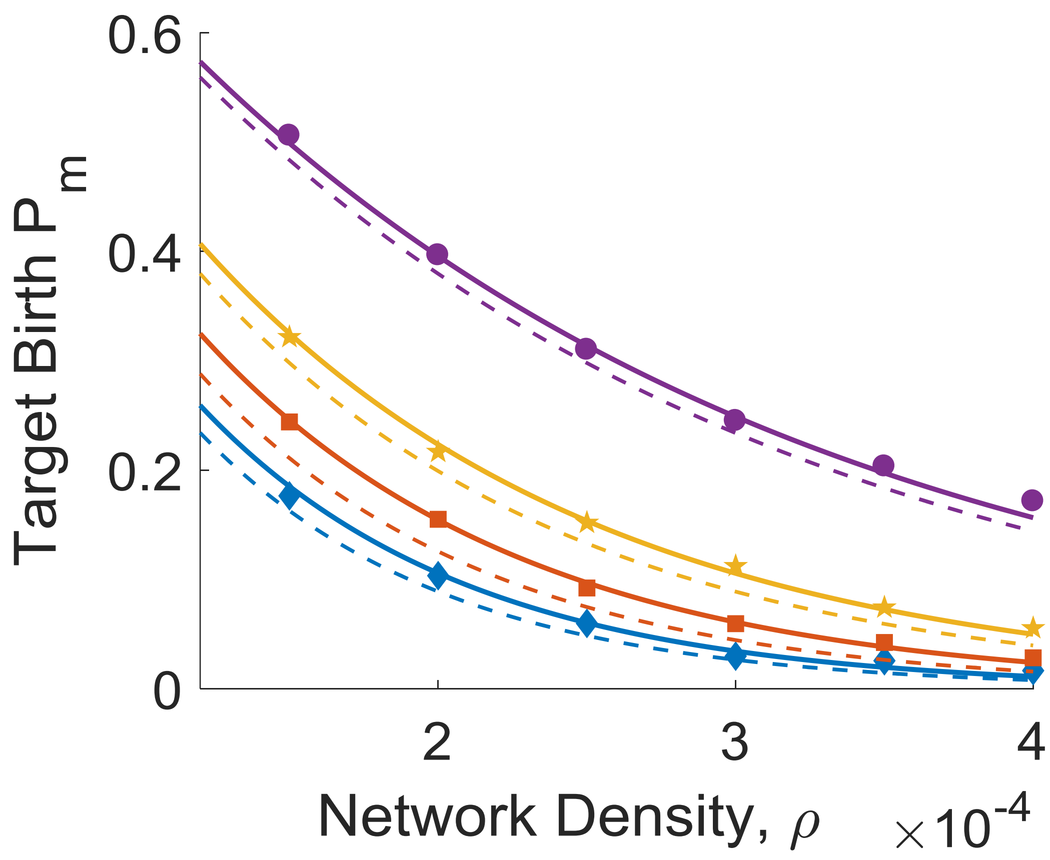
$$P_{m,mat} \geq \exp\left(-\frac{\left(\pi R_r^2 \alpha \chi \rho \left[\left(1 - p_{sleep}\right) + \frac{N_{sel}}{\rho \pi R_{s,HPS}^2}(1-\alpha)\right]\right)}{2 - p_{sleep} - \alpha}\right)$$

where $\chi = 1 + \frac{2(1+\beta R_r)}{\beta^2 R_{s,HPS}^2}\left(1 - \frac{(1+\beta R_{s,HPS})\exp(-\beta R_{s,HPS})}{(1+\beta R_r)\exp(-\beta R_r)}\right)$

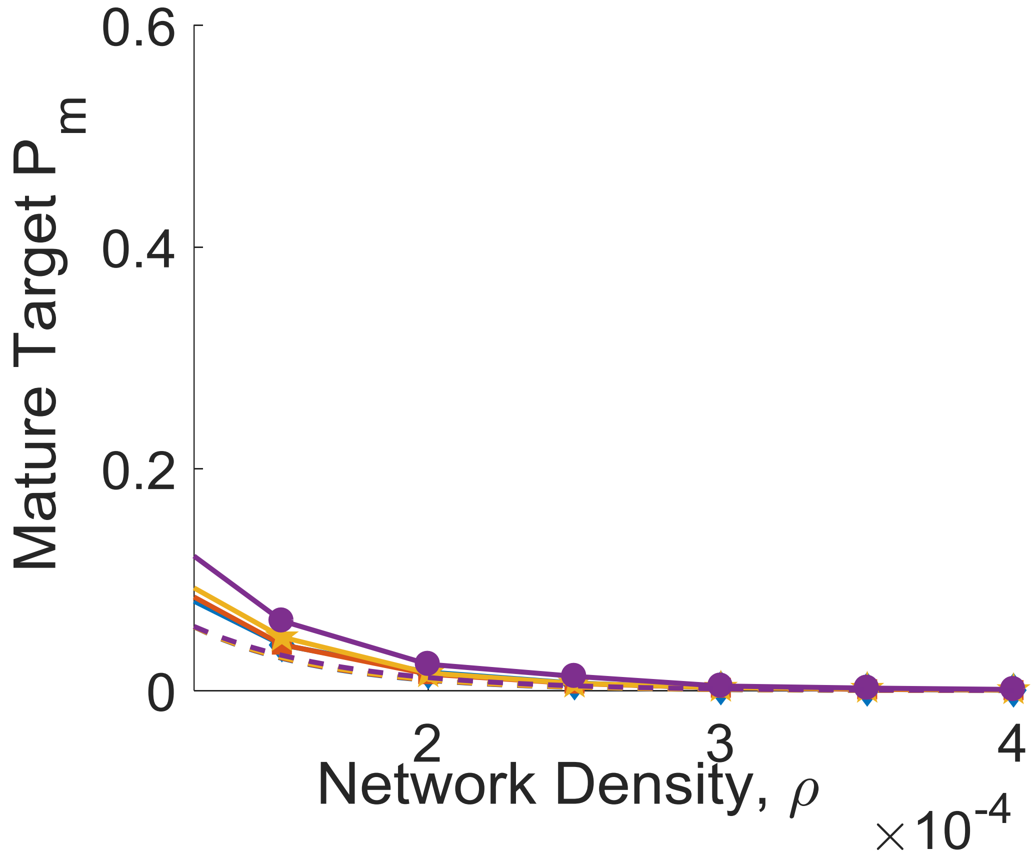
POSE.3C

Missed Detection Theorem Validation

Theorem 3a Validation: Target Birth



Theorem 3b Validation: Mature Target



Simulated

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

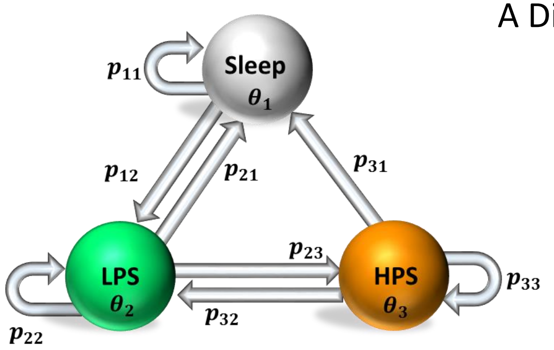
Theoretical

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

POSE.3C

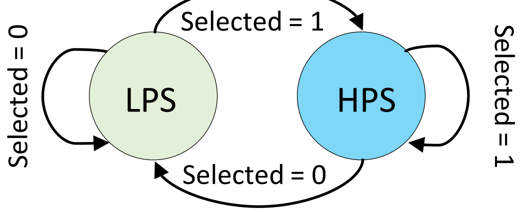
Network Lifetime Comparison

POSE.3C



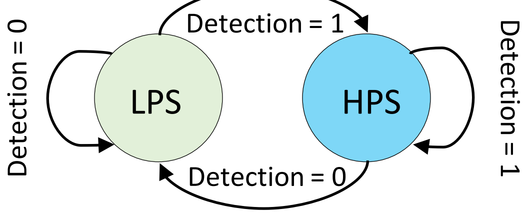
Autonomous Node Selection (ANS) [1]

A Distributed Sensor Selection Method that utilizes GDOP as the cost function



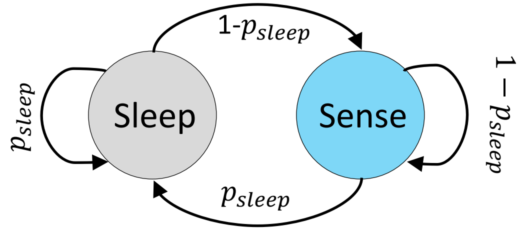
LPS-HPS Scheme

Distributed detection-based sensor activation

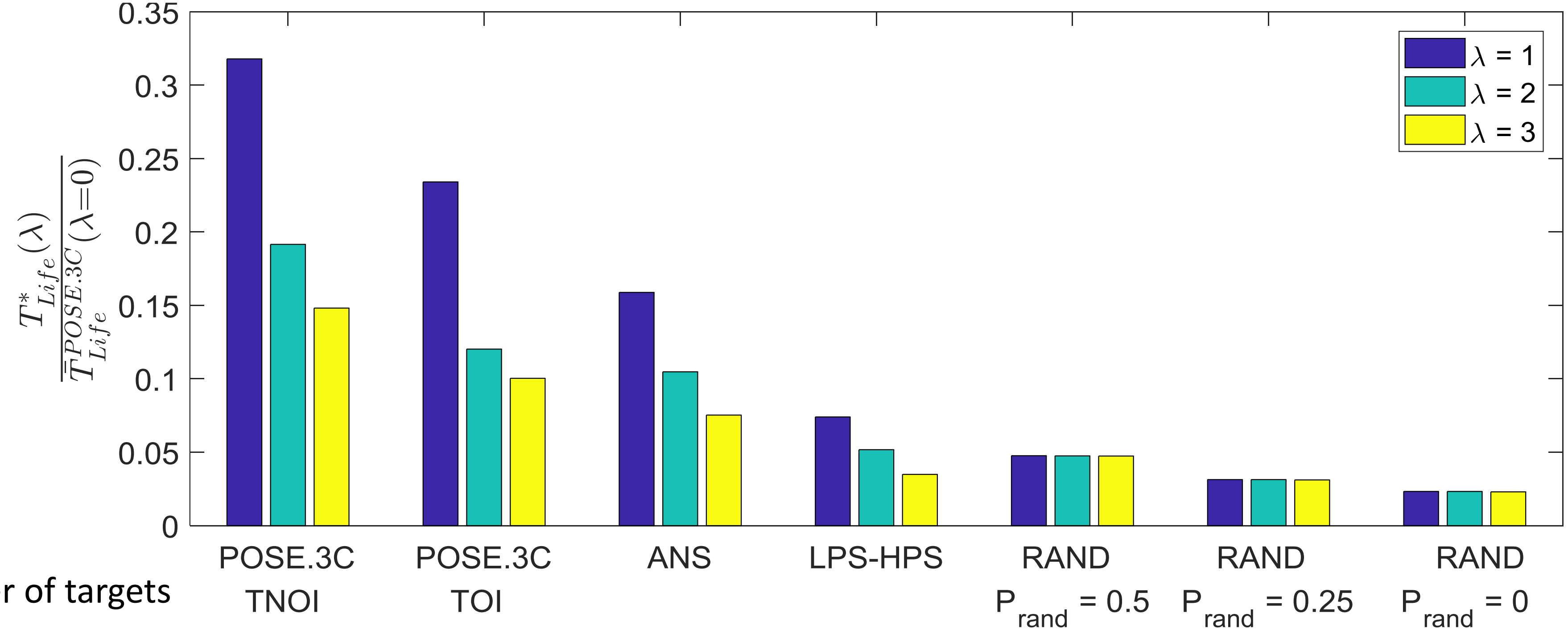


Random Scheduling Scheme

Distributed Probabilistic sensor activation.



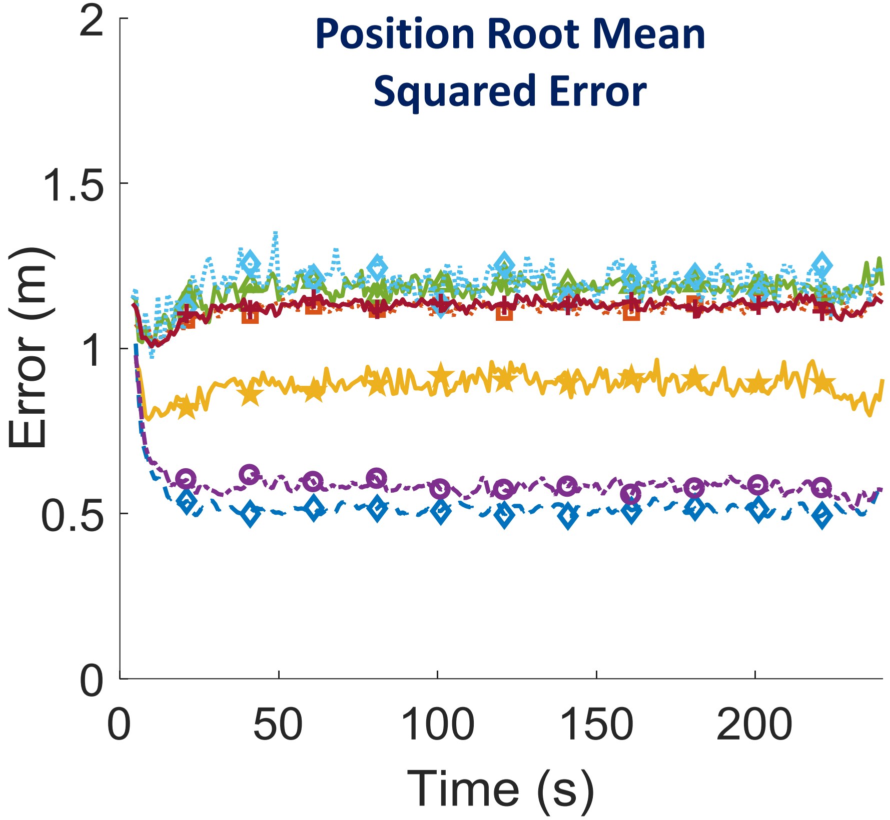
Network Lifetime Normalized by the Lifetime of the POSE.3C Network with $\lambda = 0$

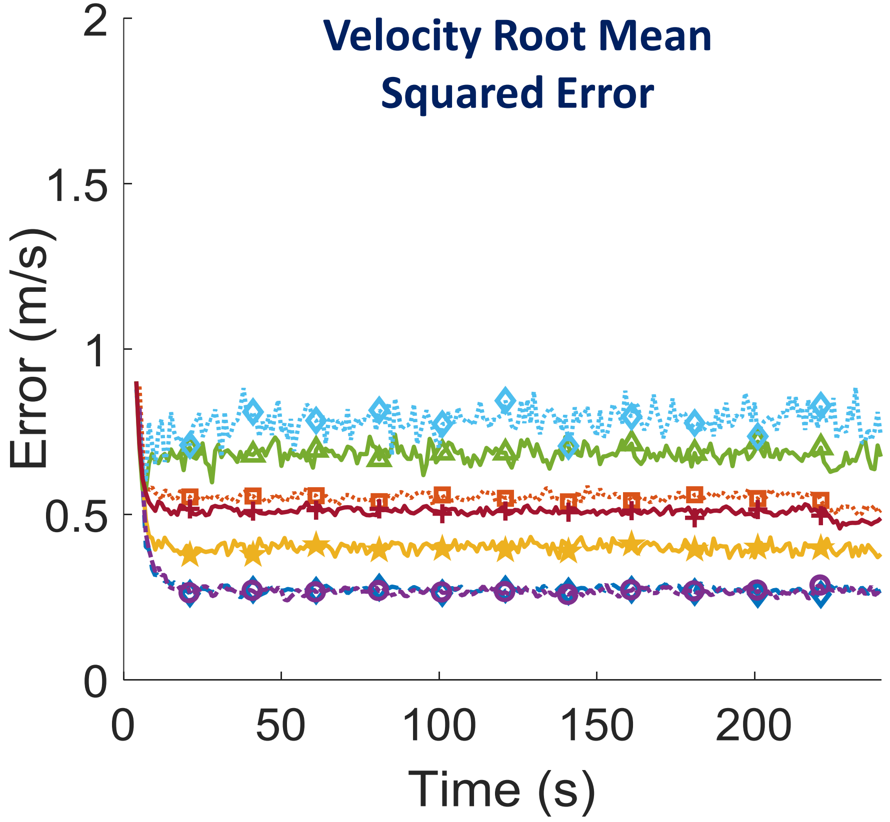


λ: Expected number of targets

POSE.3C

Estimation Error Comparison





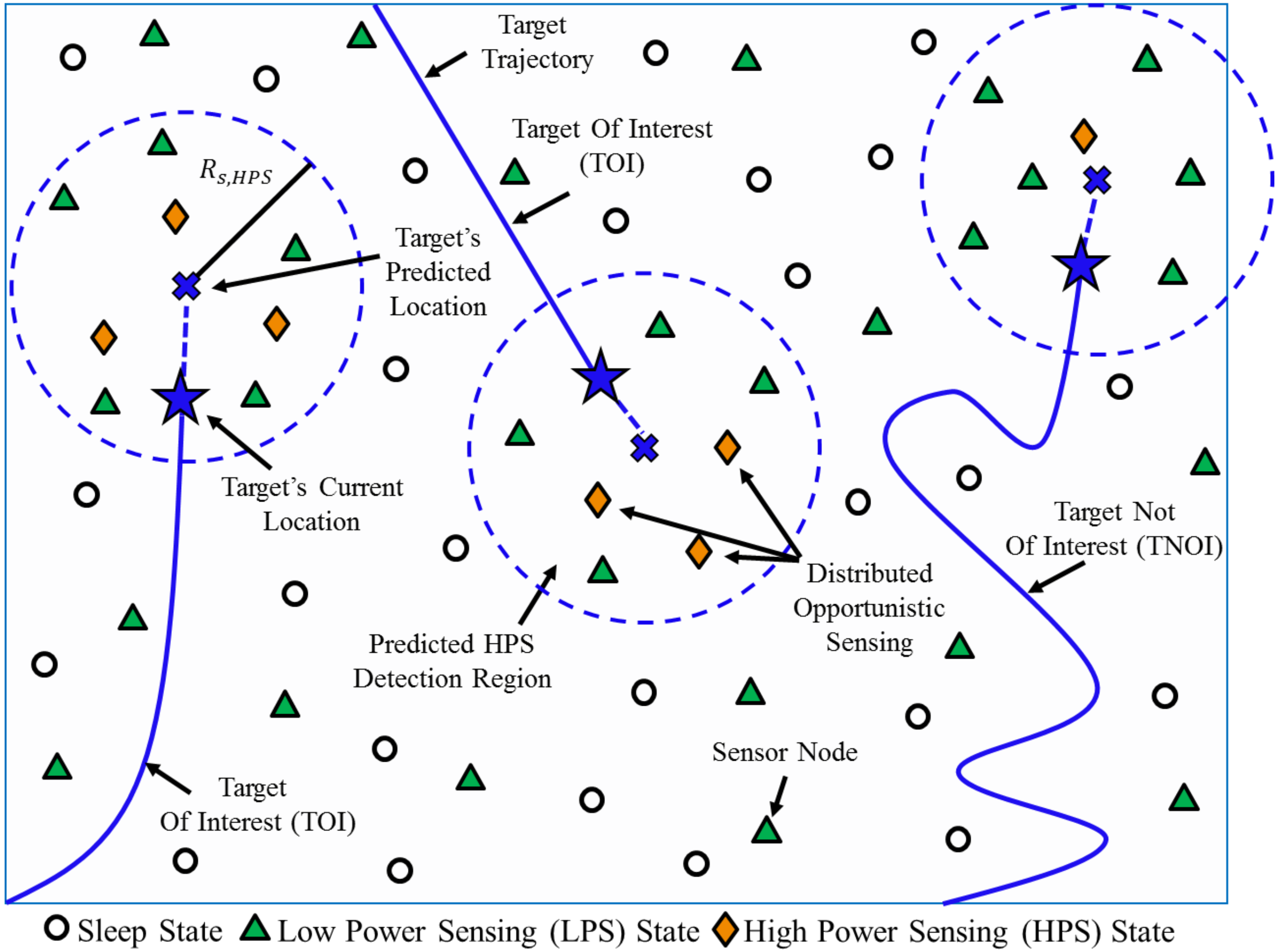
Legend

POSE.C TOI   POSE.C TNOI   ANS   LPS-HPS

RAND, $P_{rand} = 0$ RAND, $P_{rand} = 0.25$ RAND, $P_{rand} = 0.5$

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

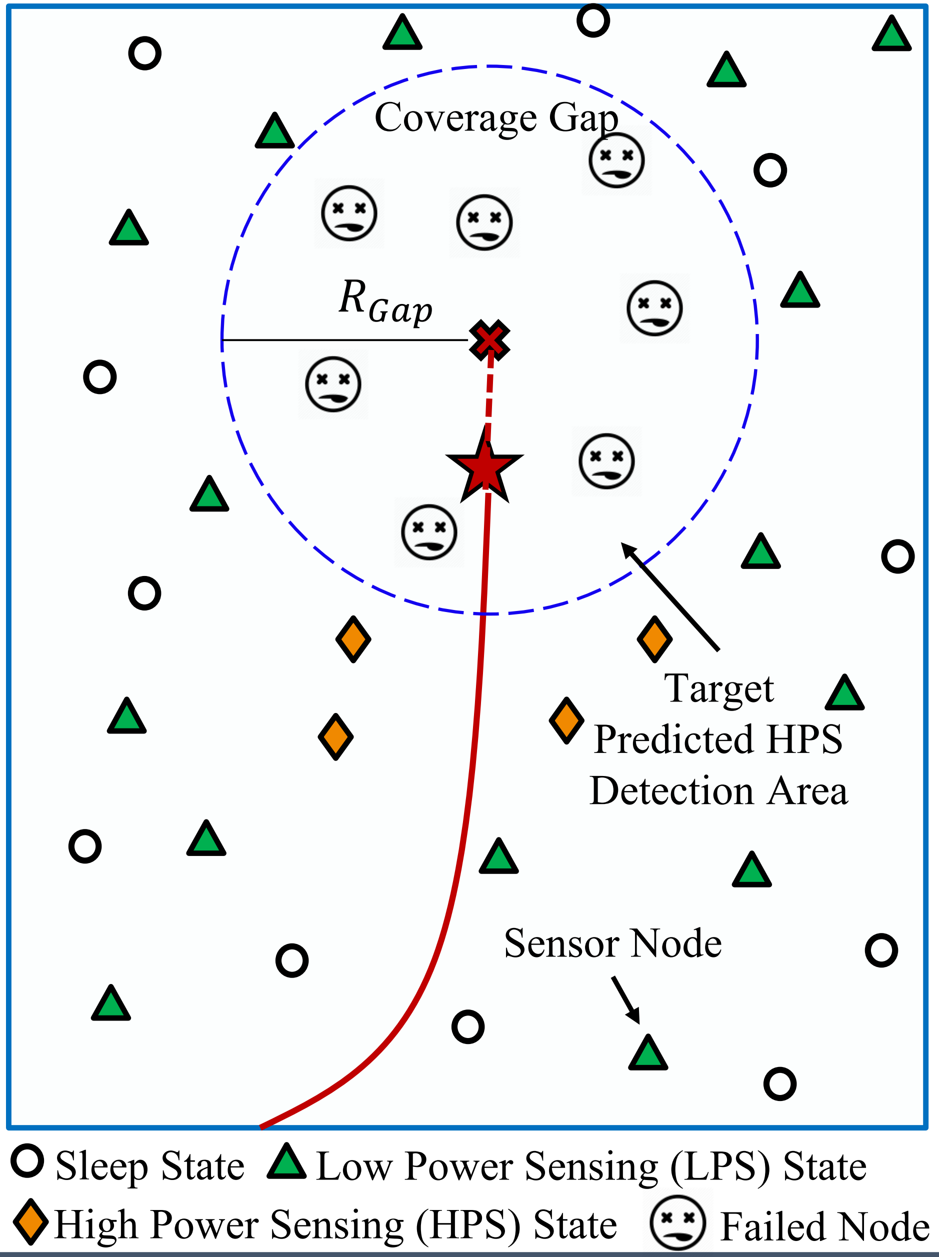
POSE.3C Algorithm Limitations:

- 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)

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

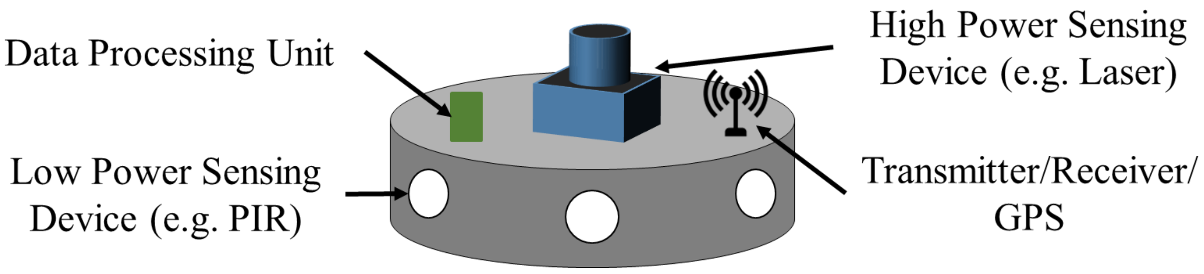


Figure: Multi-Modal Sensor Node Example

New Feature

HPS Sensing Radius

$$R_{s,HPS}^{s_i}(k) = \{R_1, \ldots, R_L\}$$

- Range can be expanded at the cost of energy

Energy Model

New Feature

Individual Sensor node energy consumption [1,2]:

$$\boxed{E^{s_i}(k) = \sum_k \sum_j e_j^{s_i} \cdot \chi_j^{s_i}(k)\Delta\mathrm{T} + e_{HPS} R_{s,HPS}^{s_i}(k) \chi_{HPS}^{s_i}(k)\Delta T}$$

- $e_j^{s_i}$: 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
- $\chi_j^{s_i}(k) \in \{0,1\}$: Indicates whether the device is On or Off at time k
- ΔT: The sampling interval

Network energy consumption:

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

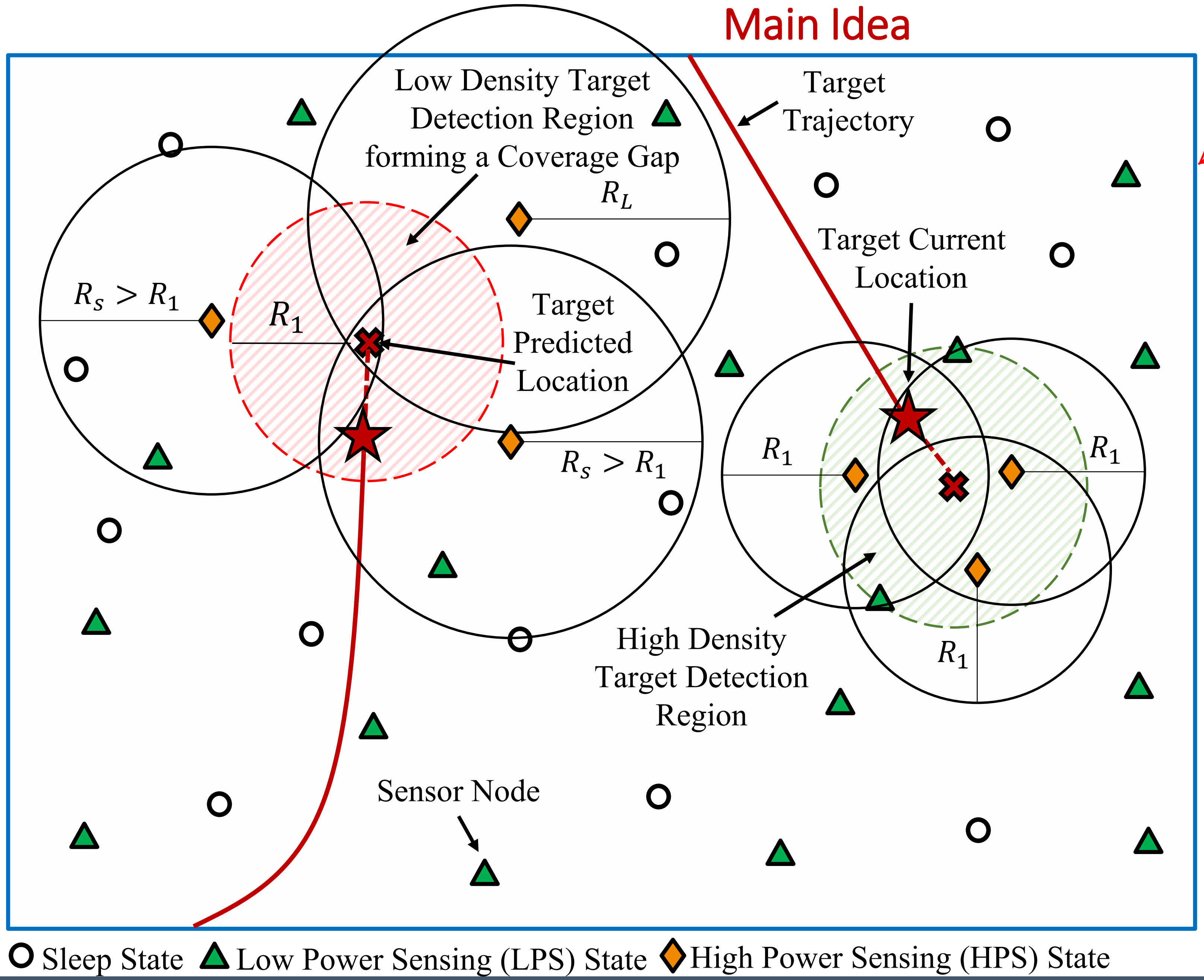
- n: Number of sensor nodes deployed

[1] J. Chen, K. Cao, K. Li, and Y. Sun, “Distributed sensor activation algorithm for target tracking with binary sensor networks,” *Cluster Computing*, vol. 14, no. 1, pp. 55–64, 2011

[2] Jia, Jie, et al. "Multi-objective optimization for coverage control in wireless sensor network with adjustable sensing radius." Computers & Mathematics with Applications 57.11 (2009): 1767-1775.

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:

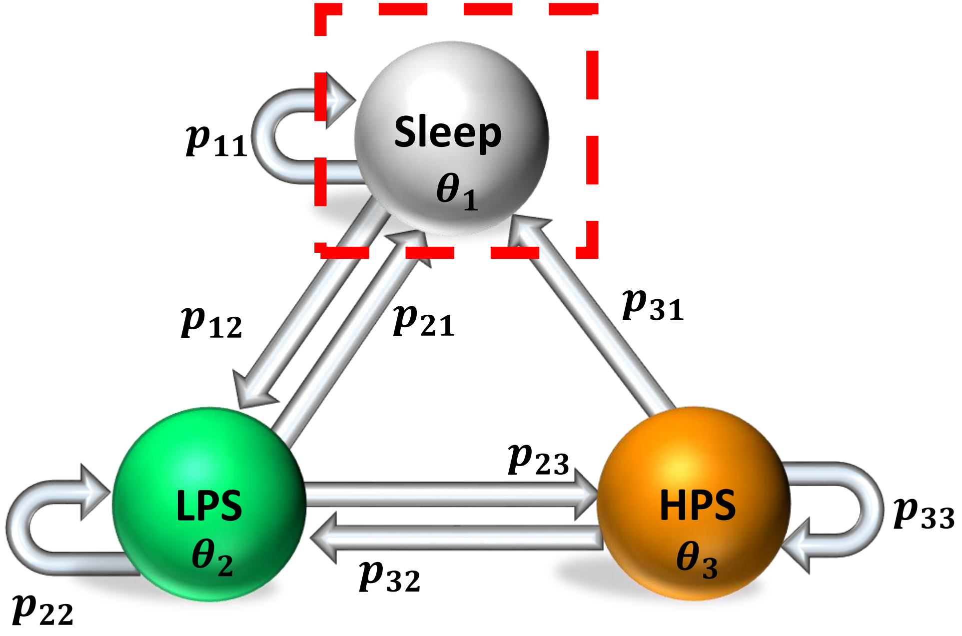
- Distributed density identification
- Distributed Clustering to ensure N_{sel} –coverage degree
- Resilient to sensor failures or sparse deployment

Target Coverage Degree

- Number of nodes covering the target with the HPS devices

POSE.R

Sleep State Algorithm



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

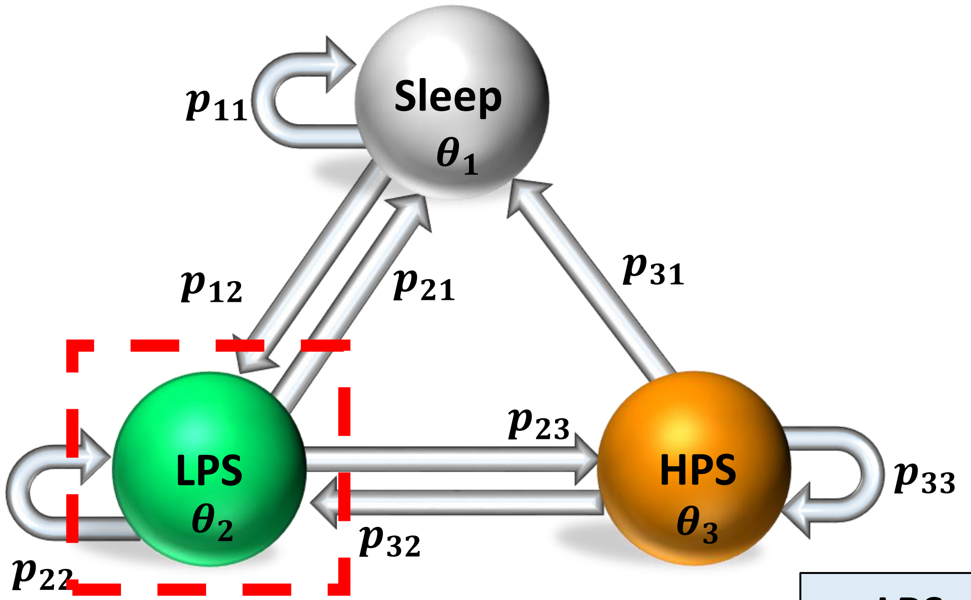
Sleep	LPS	HPS
$p_{11}^{s_i} = p_{sleep}$	$p_{12}^{s_i} = 1 - p_{sleep}$	$p_{13}^{s_i} = 0$

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

LPS: Low Power Sensing
HPS: High Power Sensing

POSE.R

Low Power Sensing (LPS) State Algorithm



New Features

- ➢ Adaptive sensor selection for resilient target coverage

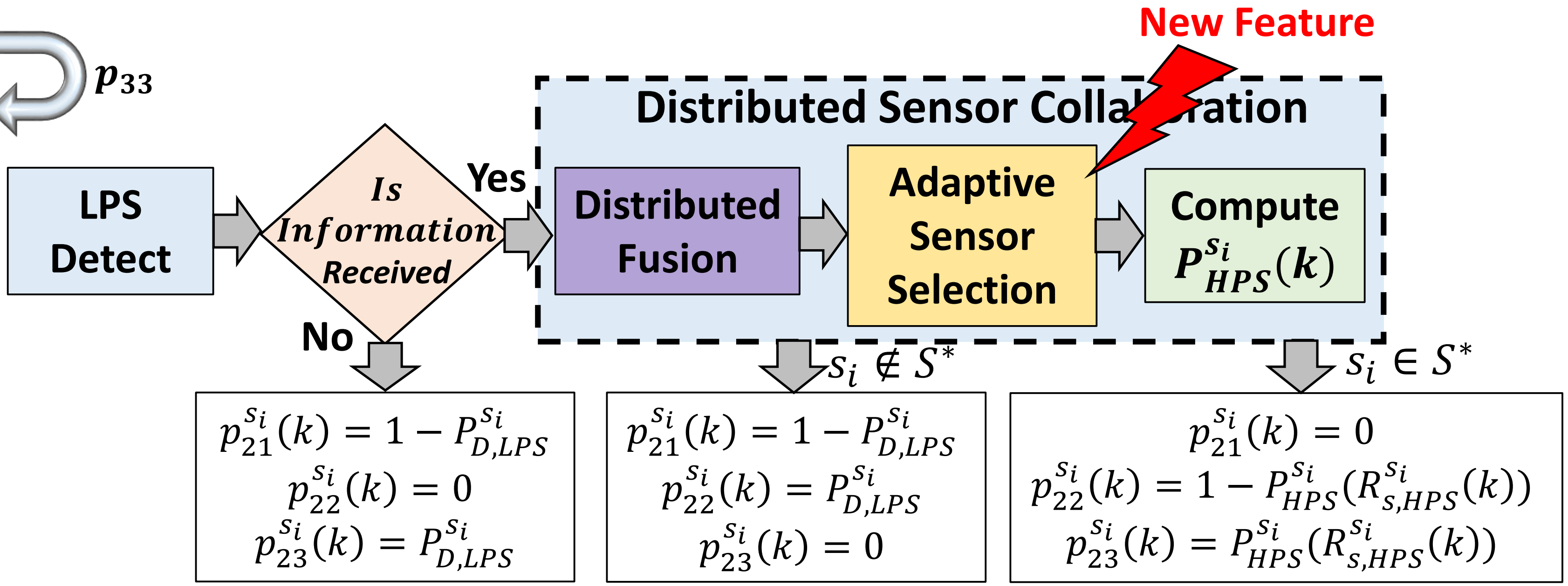


Figure: Low Power Sensing State Algorithm

Legend:

s_i: Sensor node i

$P^{s_i}_{D,LPS}$: Probability of detection of LPS Device

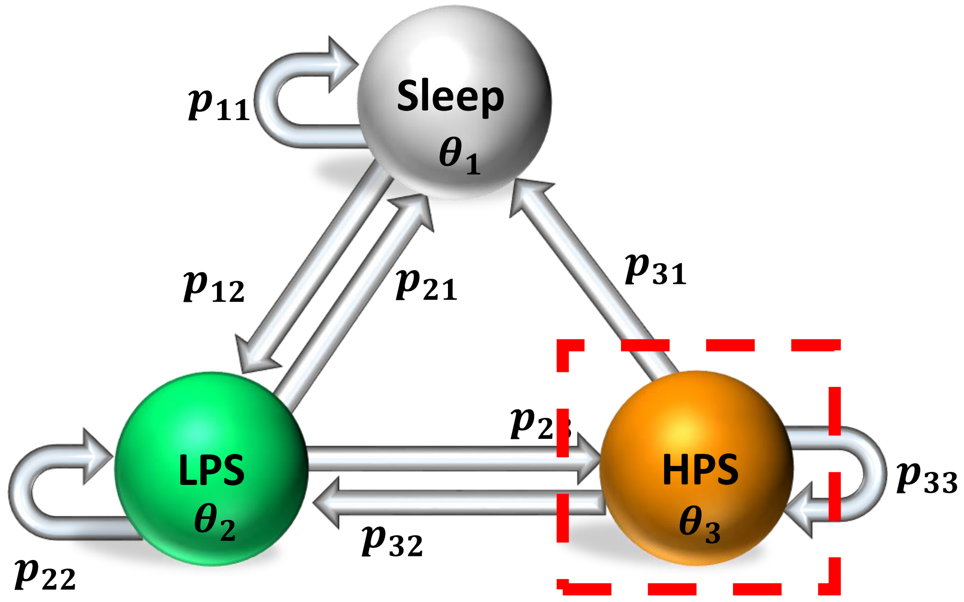
$P^{s_i}_{HPS}(k)$: Probability that the target is located in HPS coverage area

$\boldsymbol{S^*}$: Set of selected nodes

$p^{s_i}_{xy}(k)$: State transition probability from state x to state y

POSE.R

High Power Sensing (HPS) State Algorithm

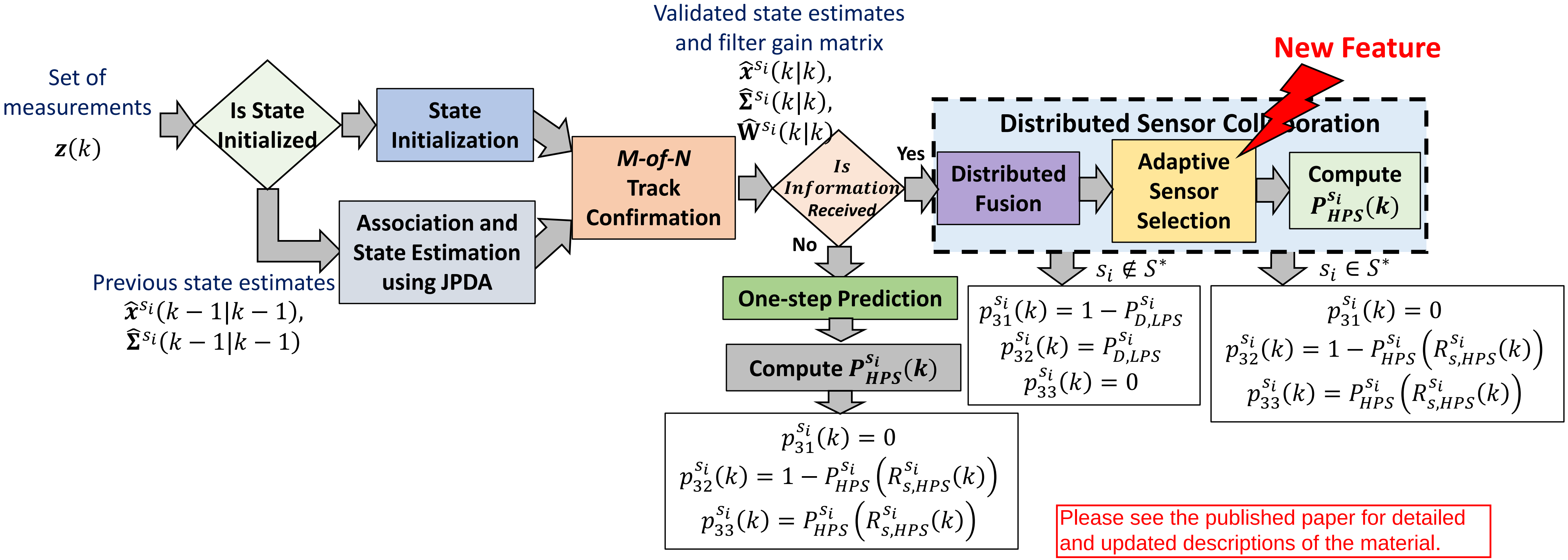


New Features

- HPS device sensing range may vary based target location and network density

POSE.R

High Power Sensing (HPS) State Algorithm



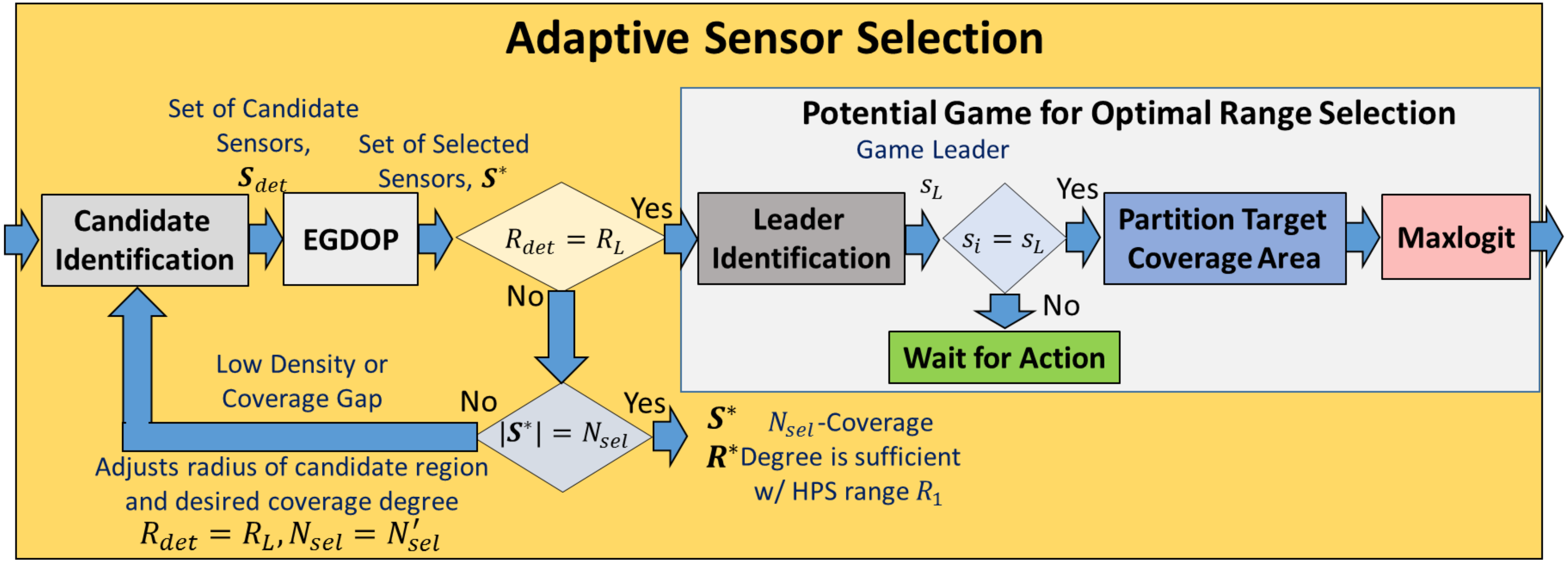
Please see the published paper for detailed and updated descriptions of the material.

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
$\boldsymbol{S}^*$: Set of selected sensors
$p_{xy}^{s_i}(k)$: State transition probability from state x to state y

POSE.R

High Power Sensing (HPS) State Algorithm

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



EGOP: Energy-based Geometric Dilution Of Precision

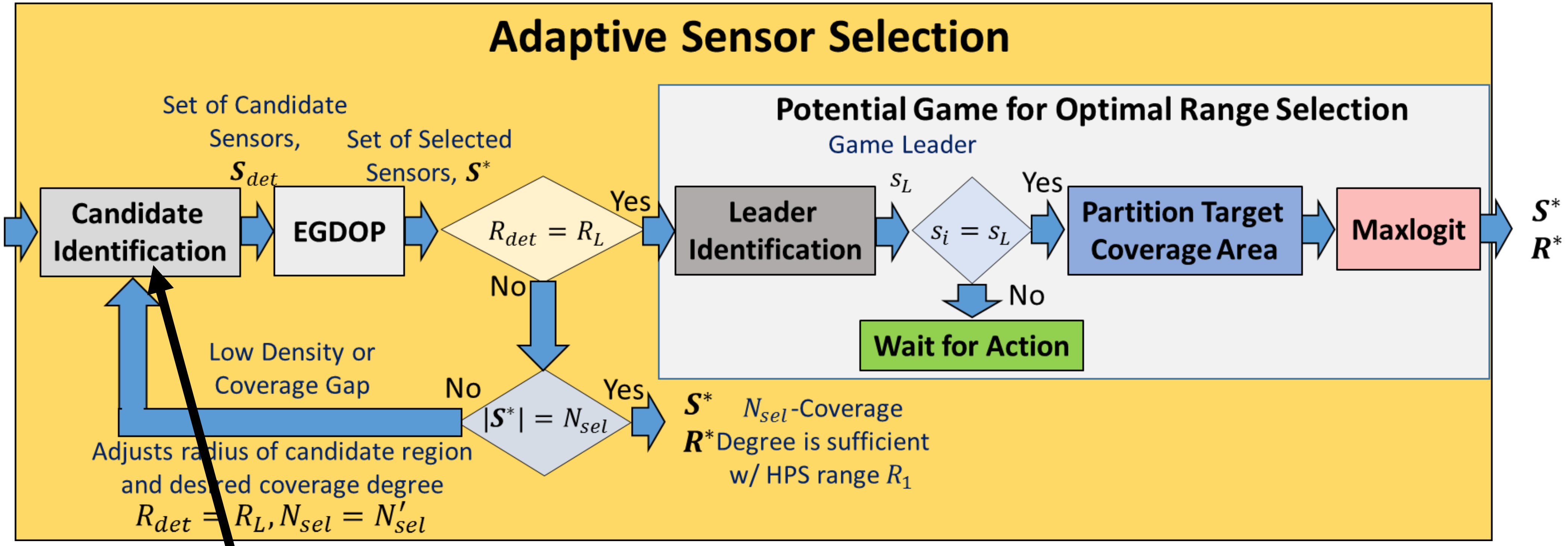
Legend:
s_i: Sensor node i
$\boldsymbol{R}^*$: Set of HPS ranges for each selected node
N'_{sel}: Number of players for range selection game

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

POSE.R

High Power Sensing (HPS) State Algorithm

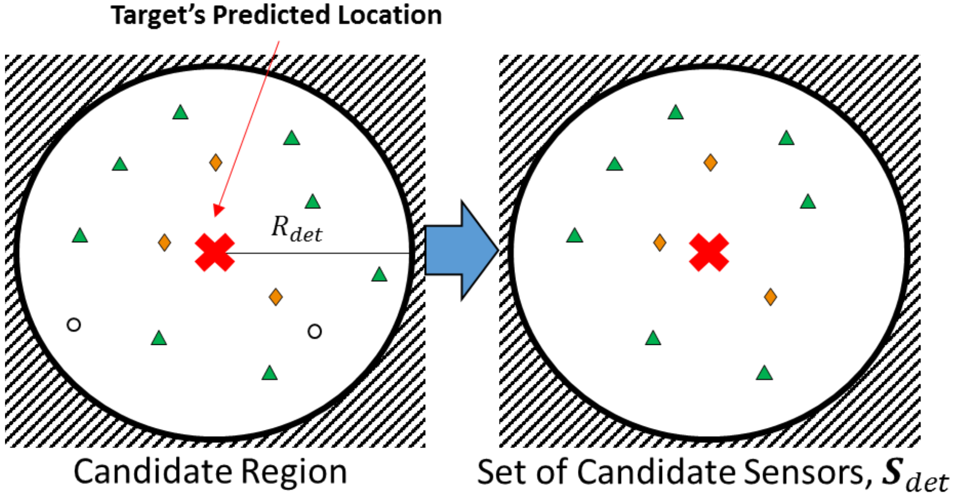
Desired Coverage Degree
N_{sel}
Predicted Target Estimate
$\hat{\boldsymbol{x}}^{s_i}(k+1|k), \hat{\boldsymbol{\Sigma}}^{s_i}(k+1|k)$
Radius of Candidate Region
$R_{det} = R_1$



EGOP: Energy-based Geometric Dilution Of Precision

Candidate Identification

Identify if node s_i is a candidate for tracking the target



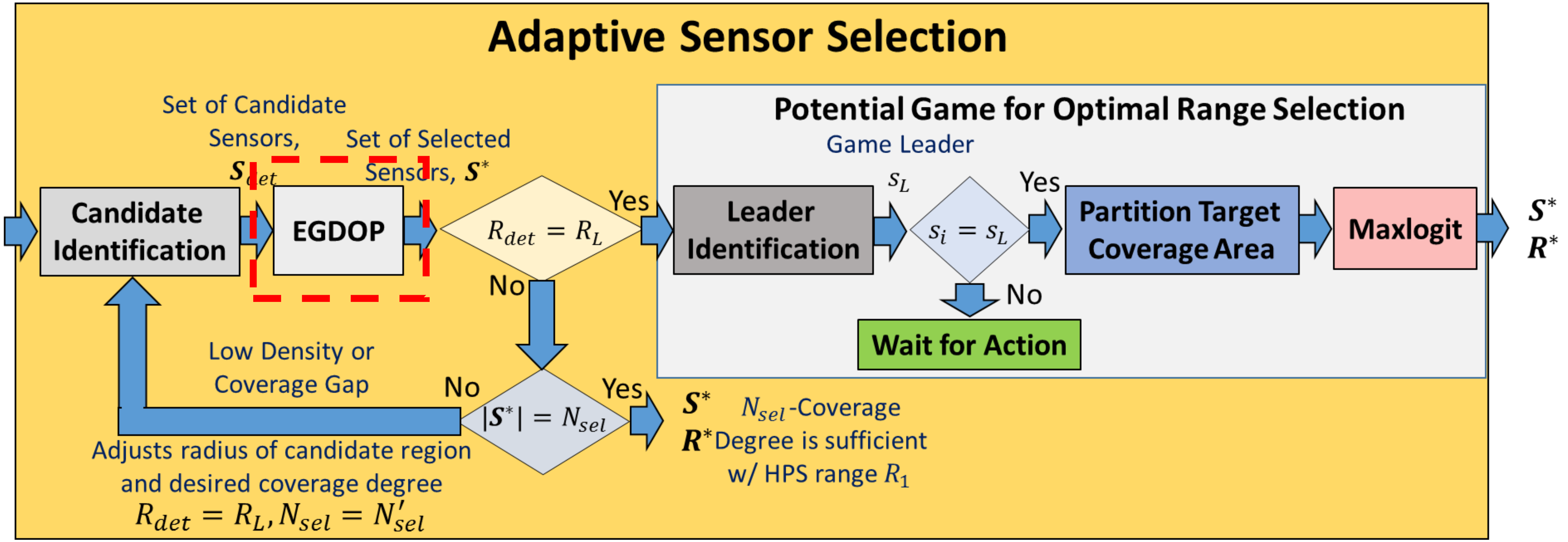
Legend:
s_i: Sensor node i
$\boldsymbol{R}^*$: Set of HPS ranges for each selected node
N'_{sel}: Number of players for range selection game

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

POSE.R

High Power Sensing (HPS) State Algorithm

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



EGOP: Energy-based Geometric Dilution Of Precision

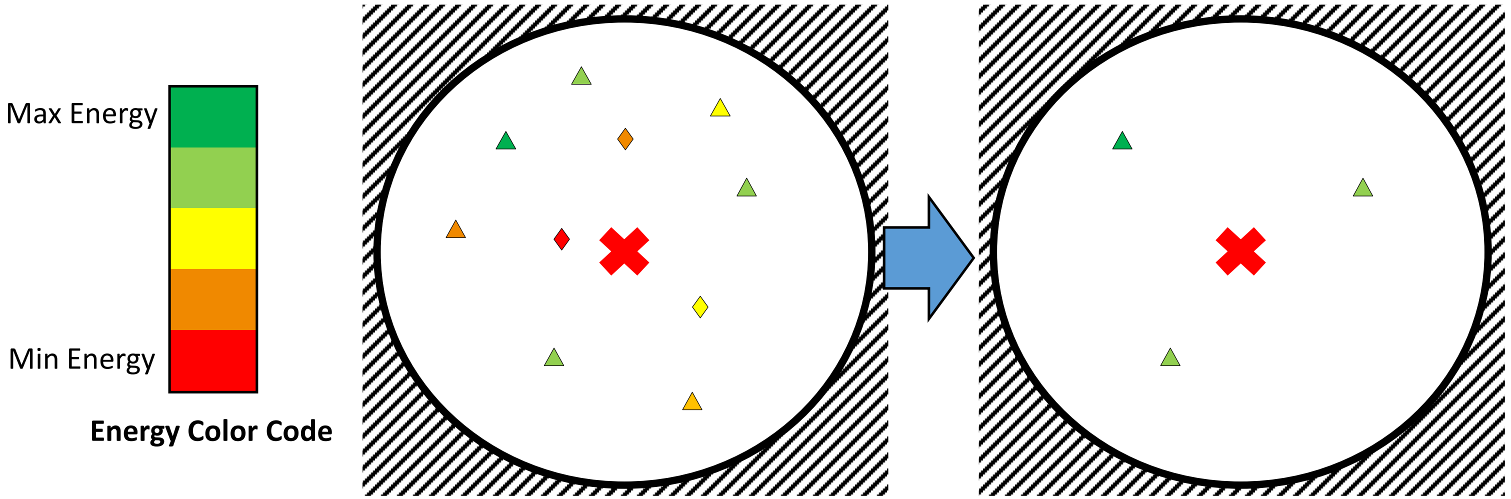
<u>Legend:</u>
s_i: Sensor node i
$\boldsymbol{R}^*$: Set of HPS ranges for each selected node
N'_{sel}: Number of players for range selection game

POSE.R

High Power Sensing (HPS) State Algorithm

Energy-based Geometrical Dilution Of Precision (EGDOP)

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



Set of Candidate Sensors, $\boldsymbol{S}_{det}$ Set of Selected Sensors, $\boldsymbol{S}^*$

Key difference between EGDOP and GDOP:

- GDOP minimizes the predicted covariance and does not use energy
- EGDOP scales predicted covariance with energy remaining

Process:

Fisher Information Matrix

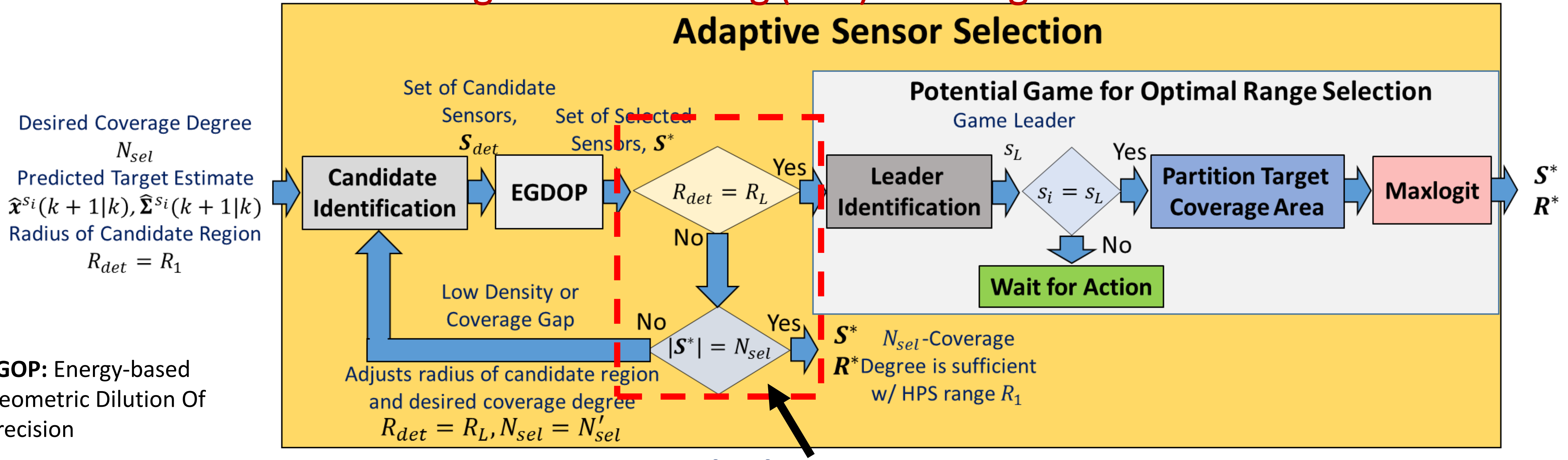
$$\mu(\tilde{\boldsymbol{S}}) = \frac{\det\left(\boldsymbol{J}(\tilde{\boldsymbol{S}})\right)}{trace\left(\boldsymbol{J}(\tilde{\boldsymbol{S}})\right)}, \qquad \boldsymbol{J}(\tilde{\boldsymbol{S}}) = \sum_{s_j \in \tilde{\boldsymbol{S}}} \frac{E_R^{s_j}}{\sigma_{\phi,norm}^2 r_{s_j,norm}^2} \begin{bmatrix} \sin\left(\phi_{s_j}\right)^2 & -\sin\left(\phi_{s_j}\right)\cos\left(\phi_{s_j}\right) \\ -\sin\left(\phi_{s_j}\right)\cos\left(\phi_{s_j}\right) & \cos\left(\phi_{s_j}\right)^2 \end{bmatrix}$$

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

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

POSE.R

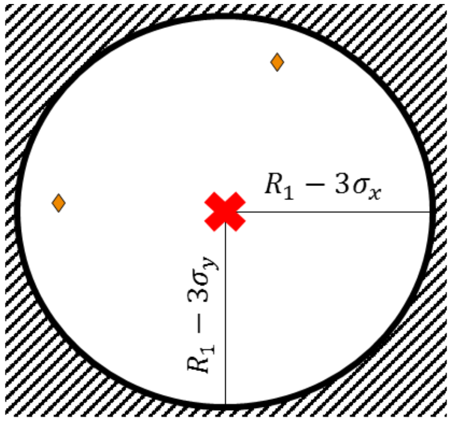
High Power Sensing (HPS) State Algorithm



EGOP: Energy-based Geometric Dilution Of Precision

Check R_1-Coverage Degree

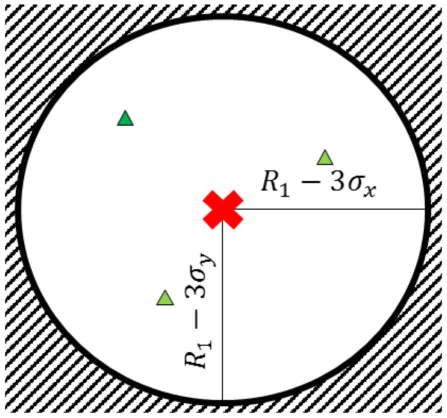
Insufficient: $< N_{sel}$ nodes in $\boldsymbol{S}^*$



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

- Identifies gap/ insufficient coverage
- Requires Expanding Candidate Region
- Optimal range selection requires

Sufficient: N_{sel} nodes in $\boldsymbol{S}^*$



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

- Sensor Selection is Complete
- $R^* = \{R_1 | \forall s_j \in \boldsymbol{S}^*\}$

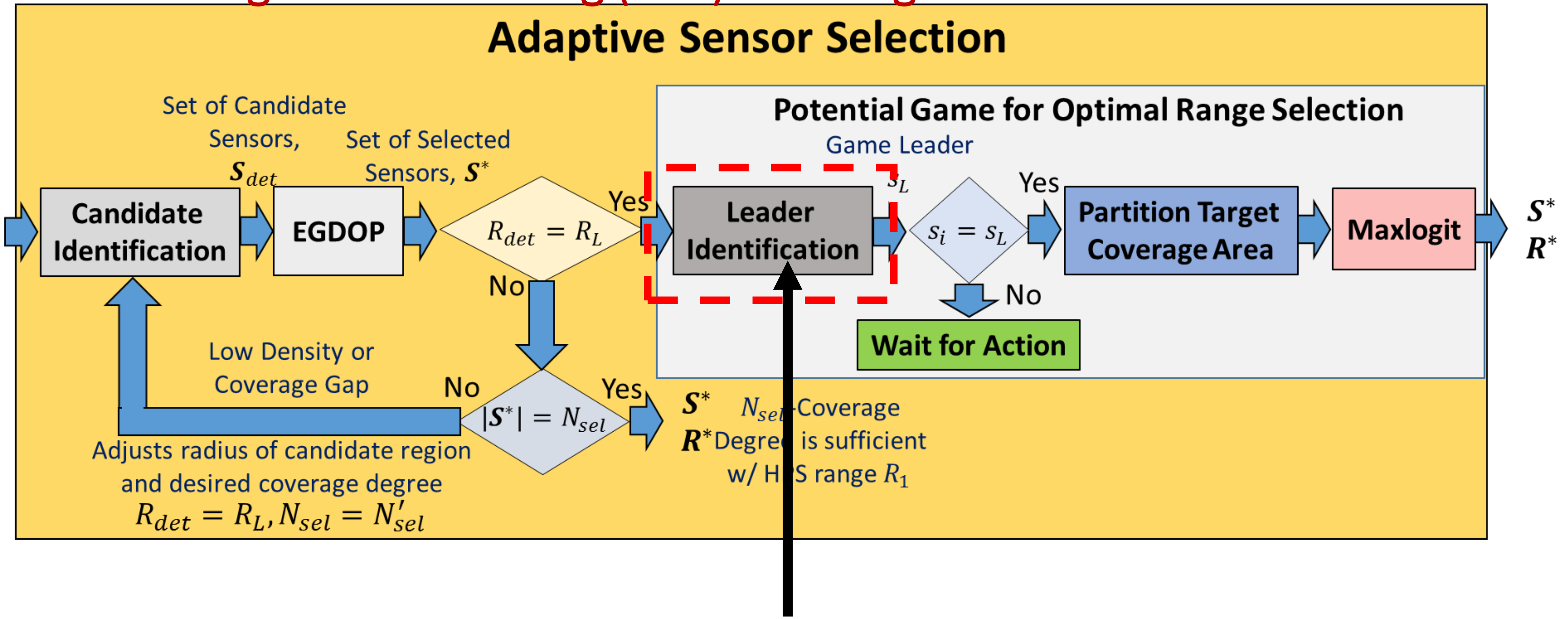
Please see the published paper for detailed and updated descriptions of the material.

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

POSE.R

High Power Sensing (HPS) State Algorithm

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



EGOP: Energy-based Geometric Dilution Of Precision

Leader Identification

Identify the Game coordinator to identify the players actions.

$$s_L = \underset{s_j}{\operatorname{argmax}}\, \boldsymbol{E}_{\boldsymbol{r}}^{s_j}$$

Where $\boldsymbol{E}_{\boldsymbol{r}}^{s_j}$ is the energy remaining of node s_j

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

POSE.R

High Power Sensing (HPS) State Algorithm

Desired Coverage Degree
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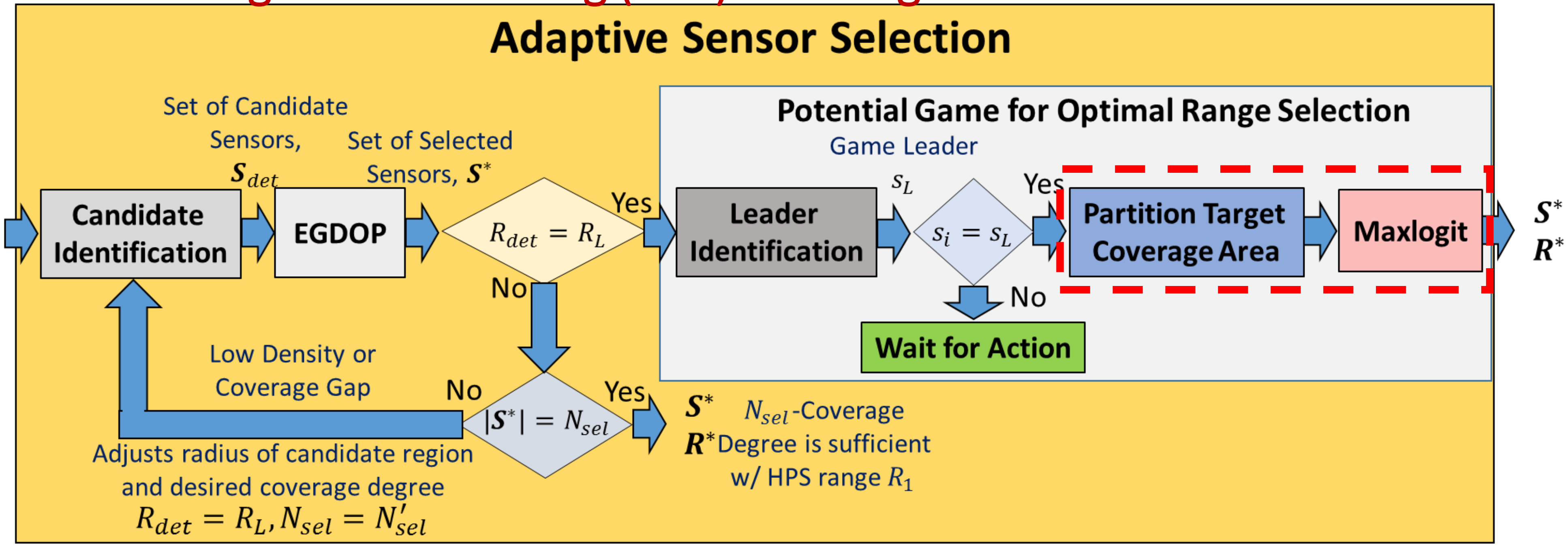
$\hat{\boldsymbol{x}}^{s_i}(k+1|k), \hat{\boldsymbol{\Sigma}}^{s_i}(k+1|k)$
Radius of Candidate Region
$R_{det} = R_1$



EGOP: Energy-based Geometric Dilution Of Precision

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

POSE.R Algorithm

Potential Game Objective

Objective: Select the optimal sensing range for each node $s_j \in \boldsymbol{S}^*$, 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, $\boldsymbol{S}^*$
- **Set of Actions:** Each action, $a_i \in A_i$, represents the nodes sensing range during the next time step, where $A_i = \{R_0, R_1, \dots, R_L\}$ 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:

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

$\forall a_i', a_i'' \in A_i$ 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

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

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

POSE.R Algorithm

Sensor Range Selection Game

Potential Function Design

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

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

Minimize selected sensing range, R^{s_j}, i.e. minimize redundant coverage

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

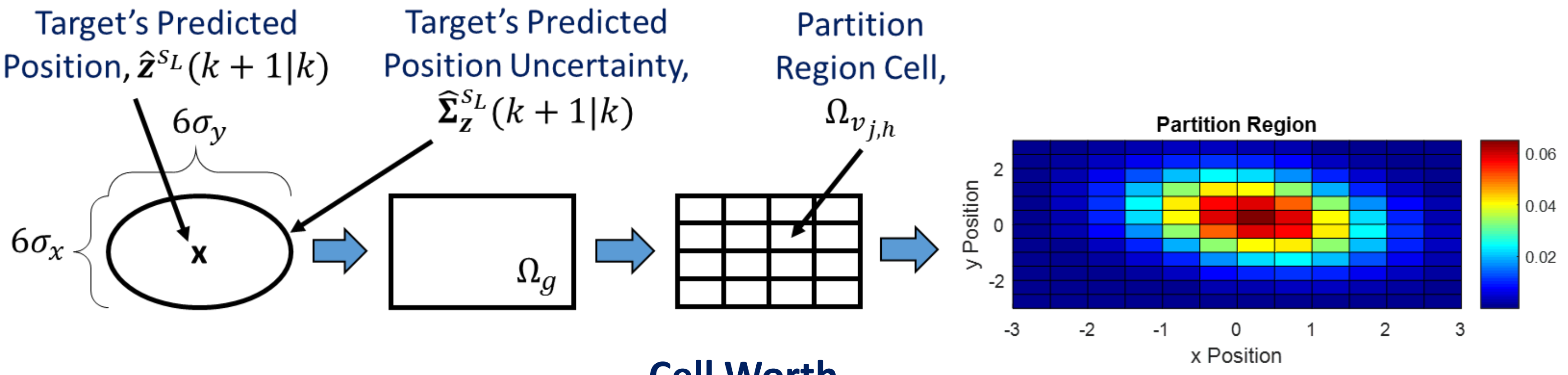
POSE.R Algorithm

Sensor Range Selection Game

Potential Function Design

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

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



Cell Worth

$$v_{j,h} = \frac{\mathcal{N}\left(\left[x_{j,h}^c, y_{j,h}^c\right]', \hat{\mathbf{z}}^{S_L}(k+1|k), \widehat{\boldsymbol{\Sigma}}_{\mathbf{z}}^{S_L}(k+1|k)\right)}{c_1}$$

- $\left[x_{j,h}^c, y_{j,h}^c\right]$: The center points of the cell $\Omega_{v_{j,h}}$
- $c_1 = \sum_{j=1}^{V}\sum_{h=1}^{V} \mathcal{N}\left(\left[x_{j,h}^c, y_{j,h}^c\right]', \hat{\mathbf{z}}^{S_L}(k+1|k), \widehat{\boldsymbol{\Sigma}}_{\mathbf{z}}^{S_L}(k+1|k)\right)$: 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

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

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

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

Coverage Function Design

$$B_{j,h}(a) = \begin{cases} 0.5 \cdot N_{B_{j,h}}(a) & if\ N_{B_{j,h}}(a) \le N_{sel} \\ 0.5\left(6 - N_{B_{j,h}}(a)\right) & if\ N_{B_{j,h}}(a) > N_{sel} \end{cases}$$

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

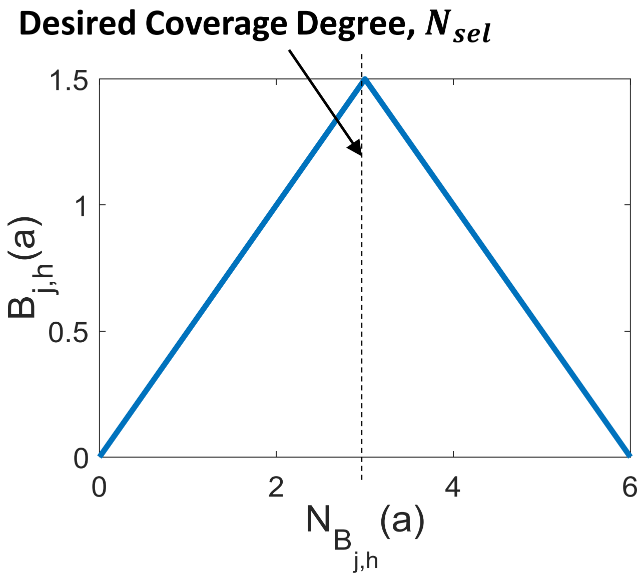


Figure: Example of Coverage Function

Coverage Function Properties

1. The coverage degree of the target's predicted position is N_{sel} if:

$$\Delta B_{j,h}(a) \ge \frac{\Delta R}{\chi|\boldsymbol{S}^*|R_L}, \forall N_{B_{j,h}}(a) \le N_{sel}$$
$$\Delta B_{j,h}(a) < \frac{\Delta R}{\chi|\boldsymbol{S}^*|R_L}, \forall N_{B_{j,h}}(a) > N_{sel}$$

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

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

$$\sum_{j=1}^{V}\sum_{h=1}^{V} v_{j,h} \ge 1 - \frac{\Delta R}{\Delta B_{j,h}(a^*)|\boldsymbol{S}^*|R_L}$$

POSE.R Algorithm

Sensor Range Selection Game

Potential Function Design

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

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

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

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

Utility Function Design using Marginal Contribution

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

$$\boxed{U_i(a_i, a_{-i}) = \sum_{j=1}^{V}\sum_{h=1}^{V} v_{j,h} \left(B_{j,h}(a_i, a_{-i}) - B_{j,h}(R_0, a_{-i})\right) - \frac{E_c(a_i) - E_c(R_0)}{|\boldsymbol{S}^*| E_c(R_L)}}$$

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

Proof:

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

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

$\square$

POSE.R

High Power Sensing (HPS) State Algorithm

Compute the Optimal Sensing Ranges using Maxlogit [1]

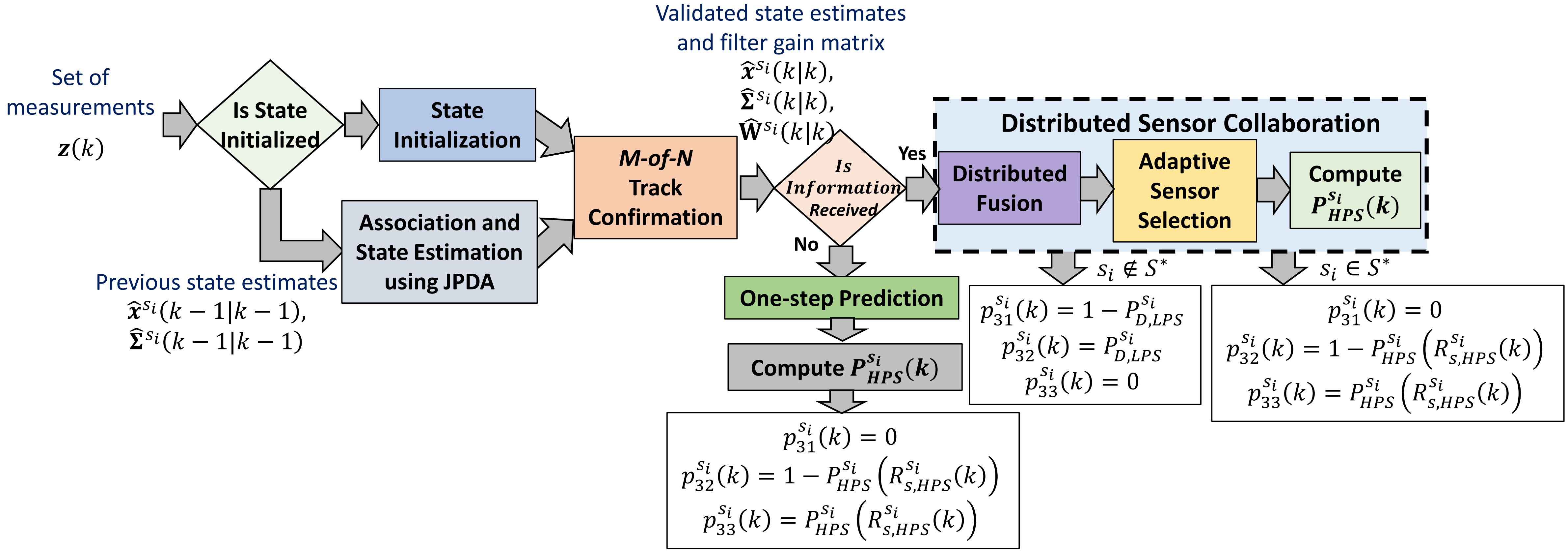
$\boldsymbol{R}^*$ is found using the Maxlogit Learning Algorithm [1]:

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: $\mu = \dfrac{e^{\frac{U_{s_i}(a_i'', a_{-i})}{\tau}}}{\max\left(e^{\frac{U_{s_i}(a_i'', a_{-i})}{\tau}}, e^{\frac{U_{s_i}(a_i', a_{-i})}{\tau}}\right)}$
    - τ: Learning parameter
4. Determine the players next action as follows: $a(s_i) = \begin{cases} a_i' \; with \Pr = 1 - \mu \\ a_i'' \quad with \Pr = \mu \end{cases}$
5. Repeat for N_{iter} iterations

[1] H. Dai, Y. Huang, and L. Yang, "Game theoretic max-logit learning approaches for joint base station selection and resource allocation in heterogeneous networks," *IEEE Journal on Selected Areas in Communications*, vol. 33, no. 6, pp. 1068–1081, 2015.

POSE.R

High Power Sensing (HPS) State Algorithm



<u>Legend:</u>

s_i: Sensor node i

$P^{s_i}_{HPS}(k)$: Probability that the target is located in HPS coverage area

$P^{s_i}_{D,LPS}$: LPS device Probability of detection

$\boldsymbol{S}^*$: Set of selected sensors

$p^{s_i}_{xy}(k)$: State transition probability from state x to state y

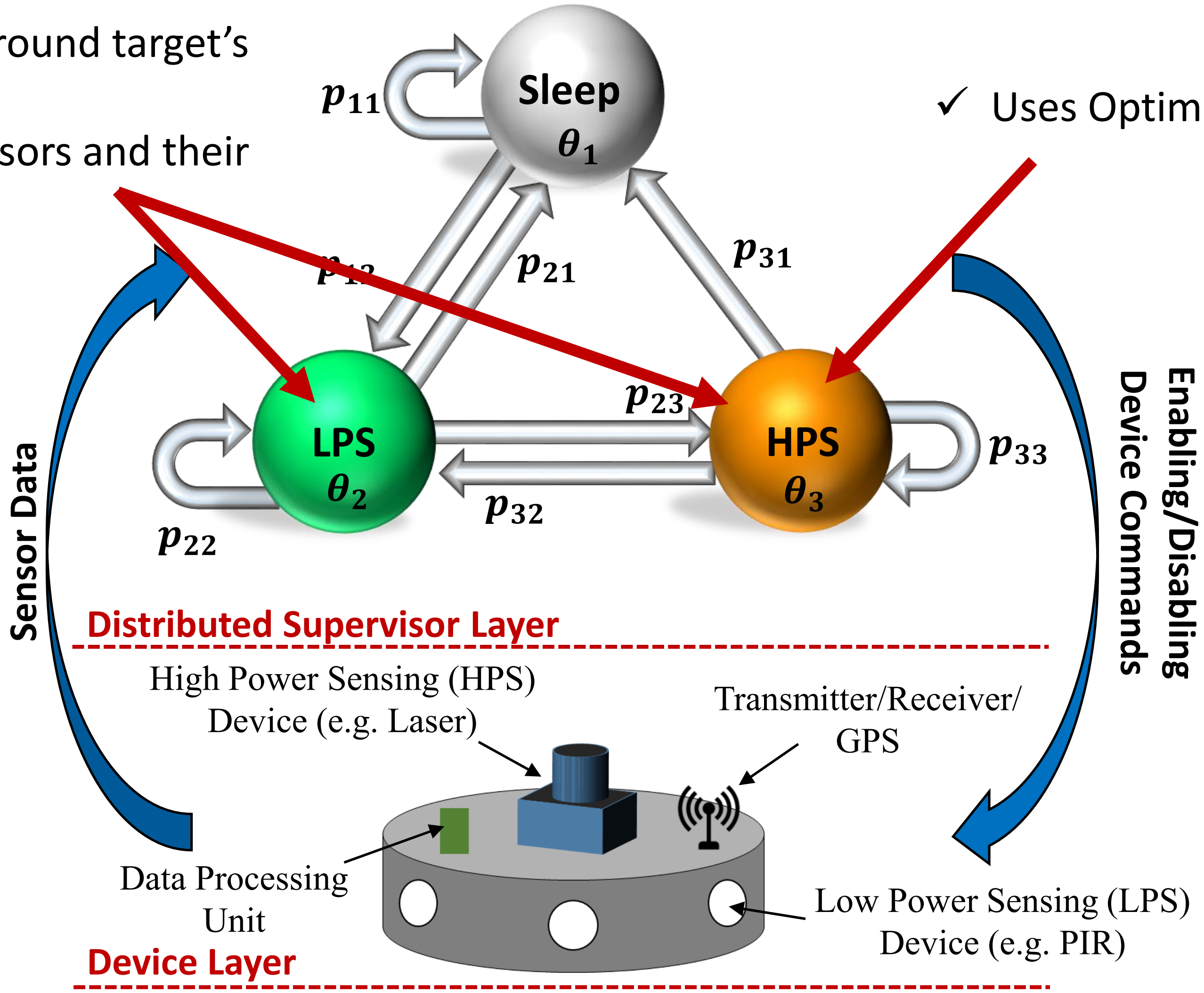
Please see the published paper for detailed and updated descriptions of the material.

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

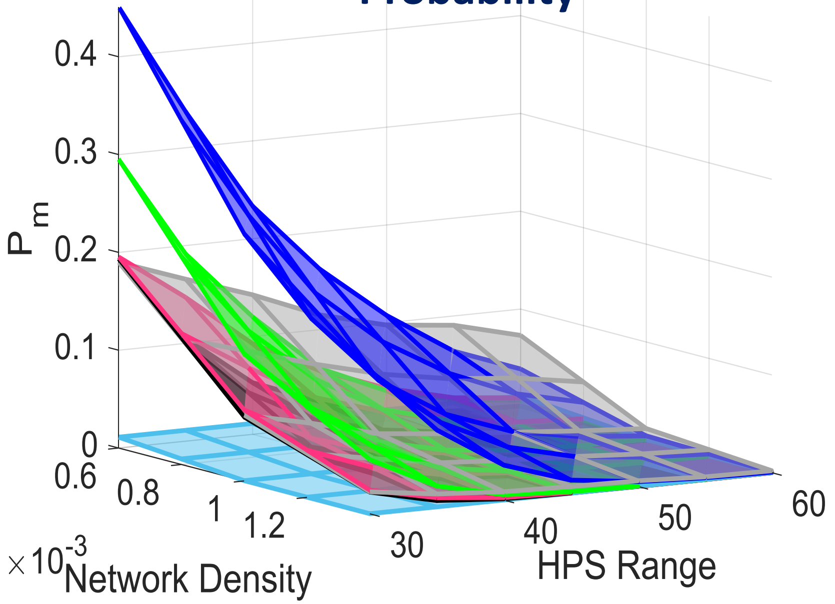


PIR: Passive Infrared Sensor

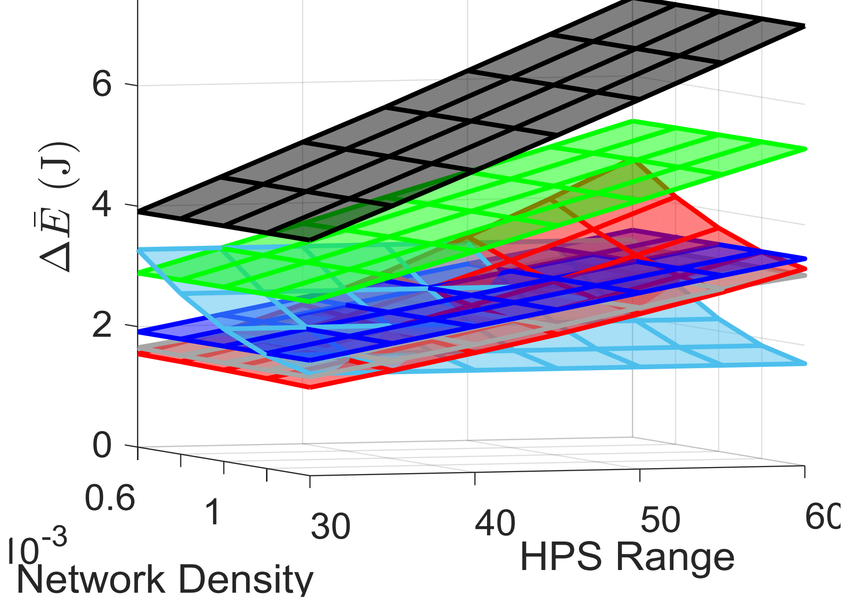
POSE.R

Characteristics Compared with Existing Techniques

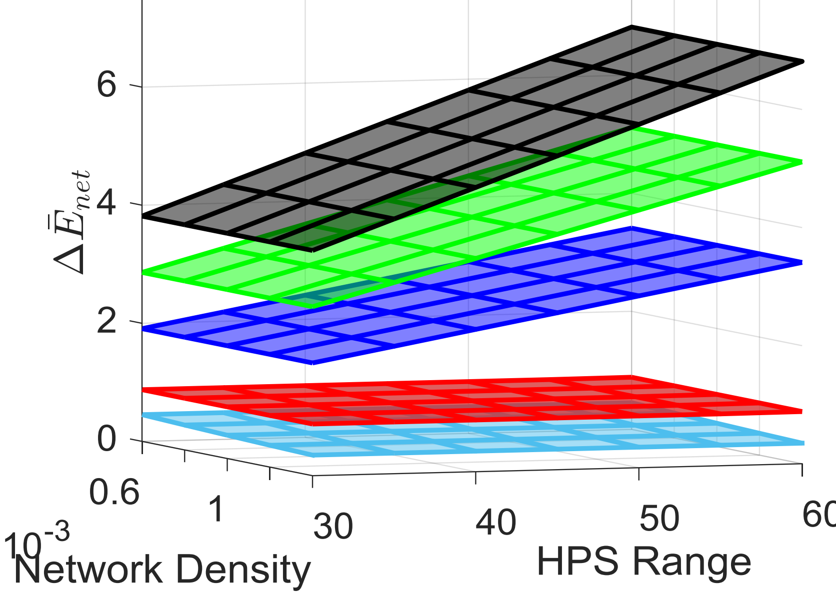
Missed Detection Probability



Avg. Energy Consumption Around Target



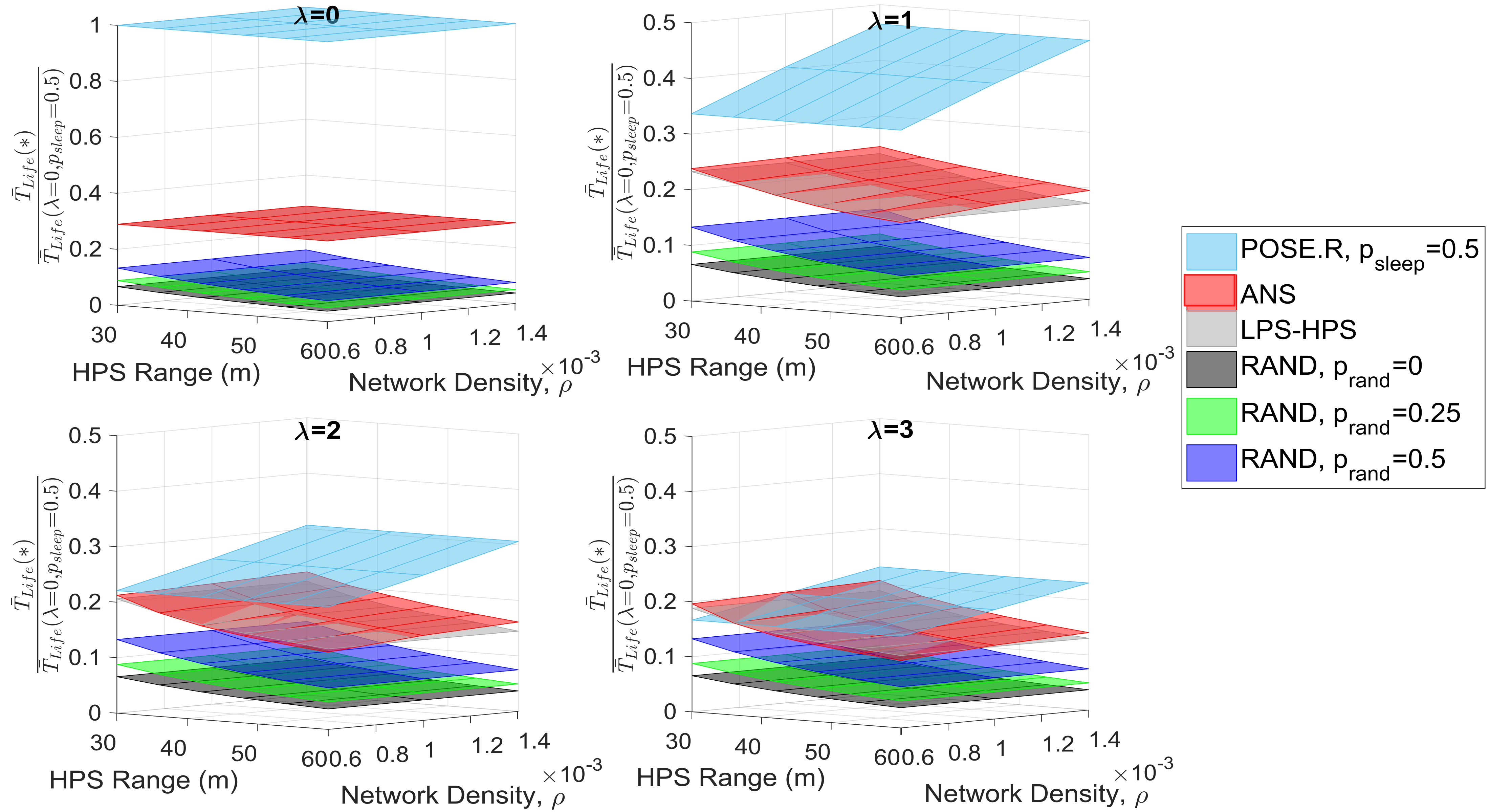
Avg. Energy Consumption Away from Target



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

POSE.R

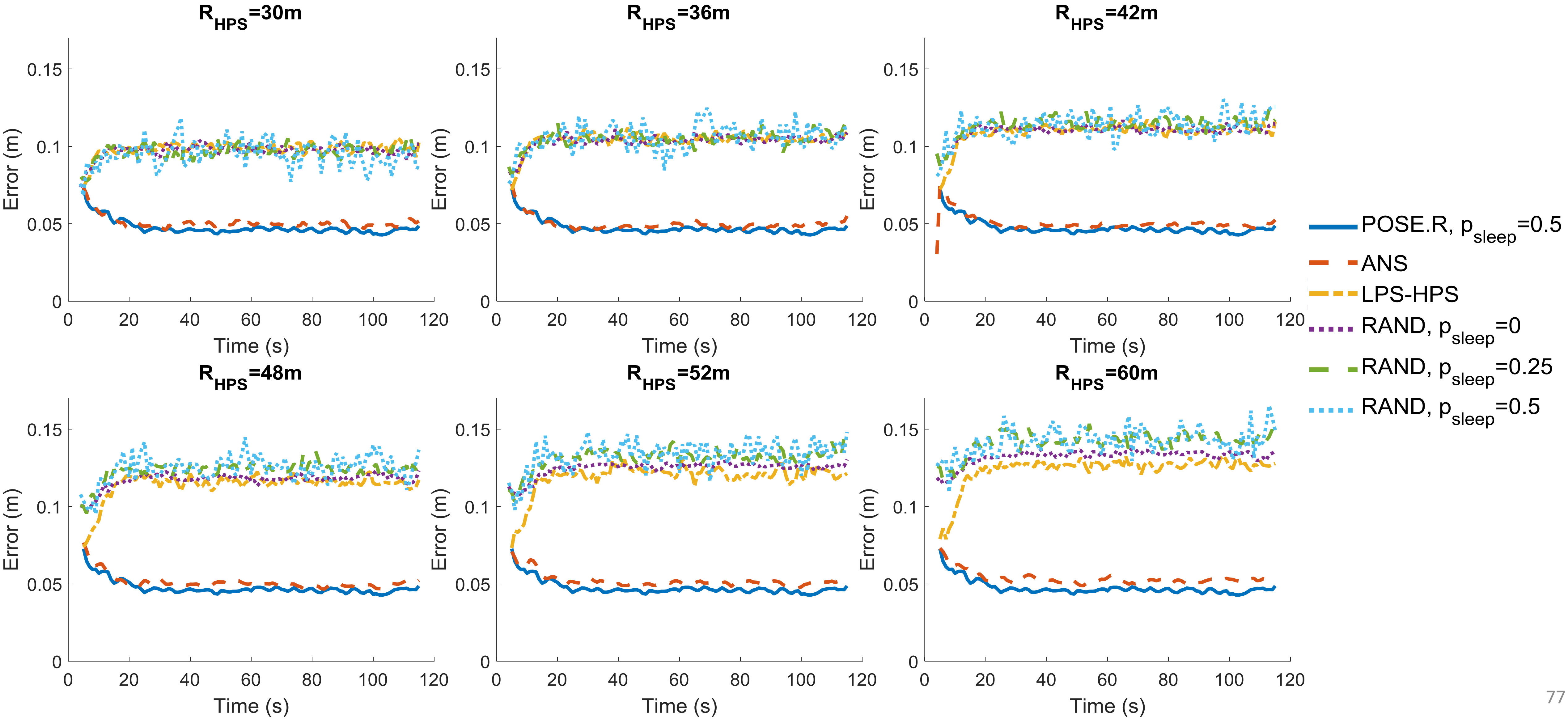
Network Lifetime Compared with Existing Techniques



POSE.R

Position Root Mean Squared Error Comparison

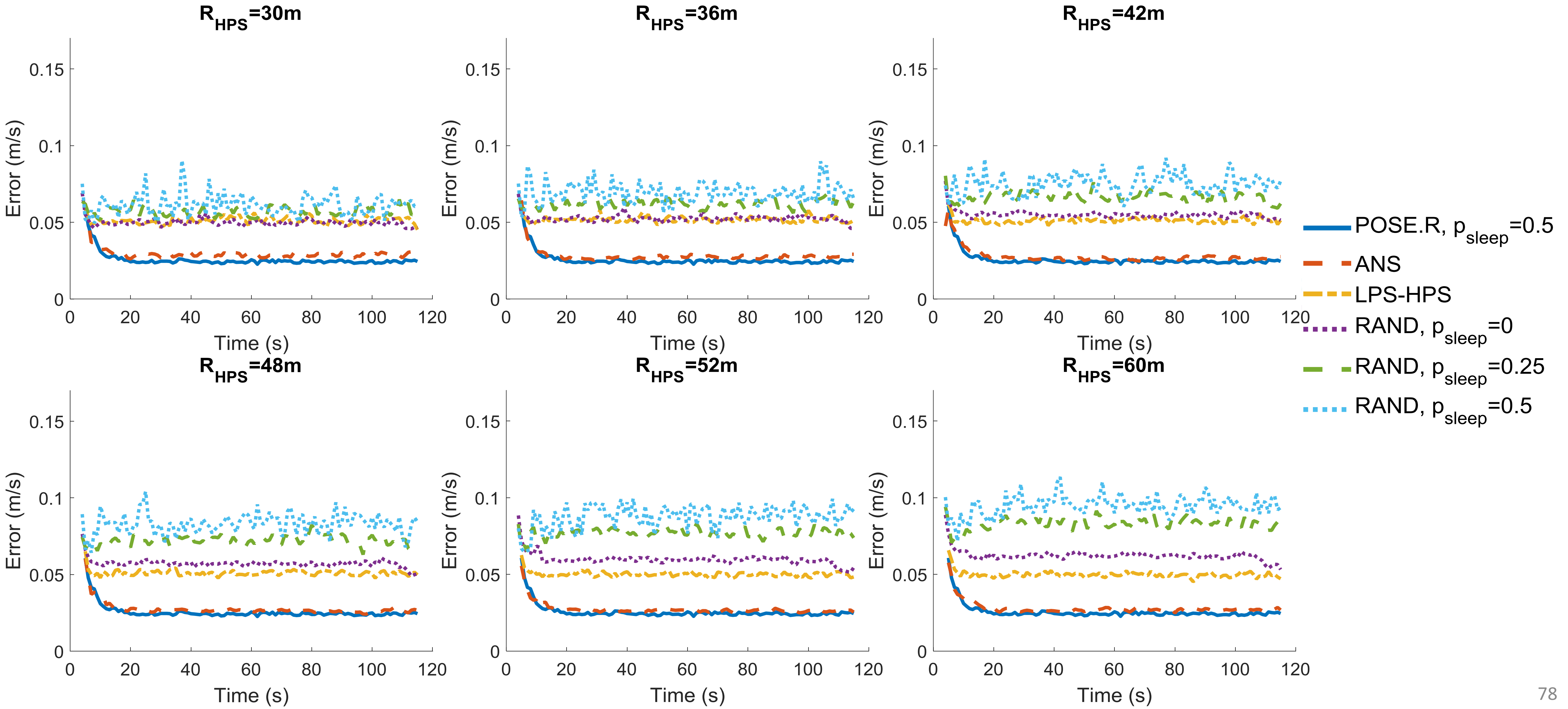
Network Density, $\rho = 1.4e^{-3}$



POSE.R

Velocity Root Mean Squared Error Comparison

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



POSE.R

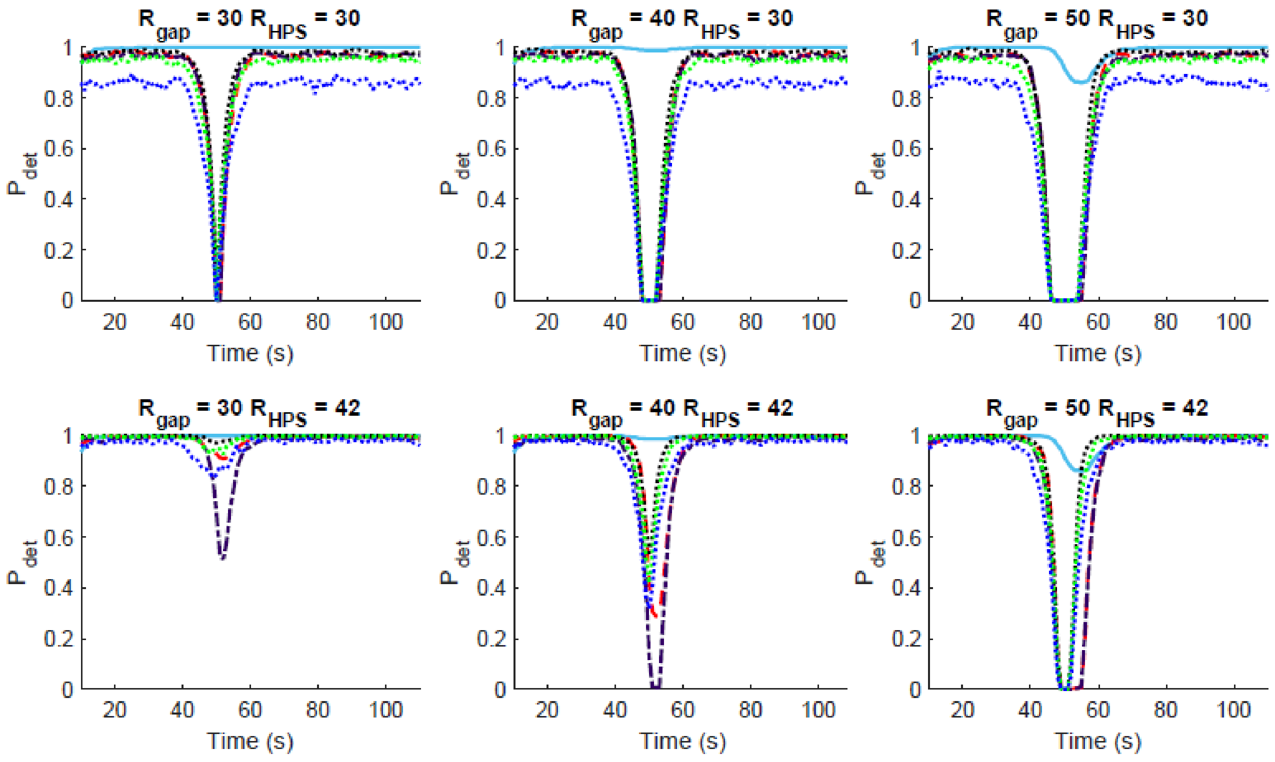
Network Resiliency Compared with Existing Techniques

Please see the published paper for detailed explanations of the results.

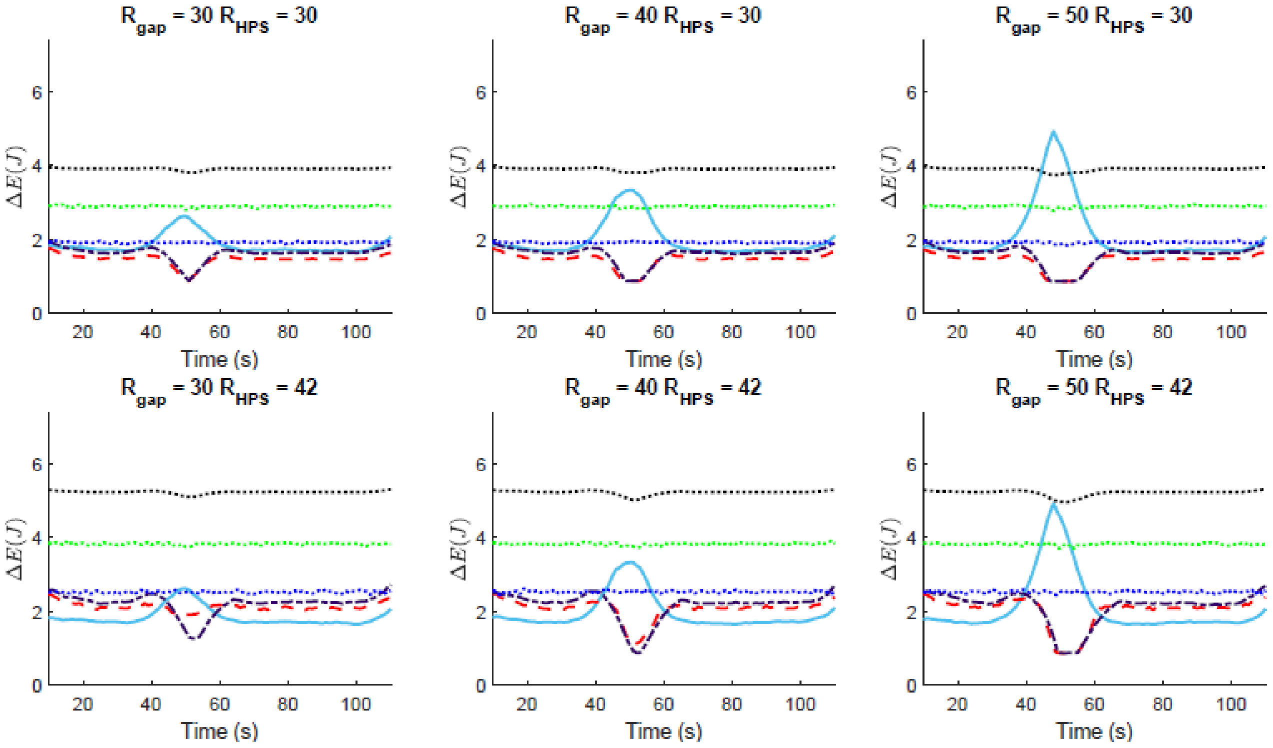
All nodes within a radius R_{gap} of the targets position at $k = 50s$ have failed

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

Probability of Detection vs. Time



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



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

POSE.R

Network Resiliency Compared with Existing Techniques

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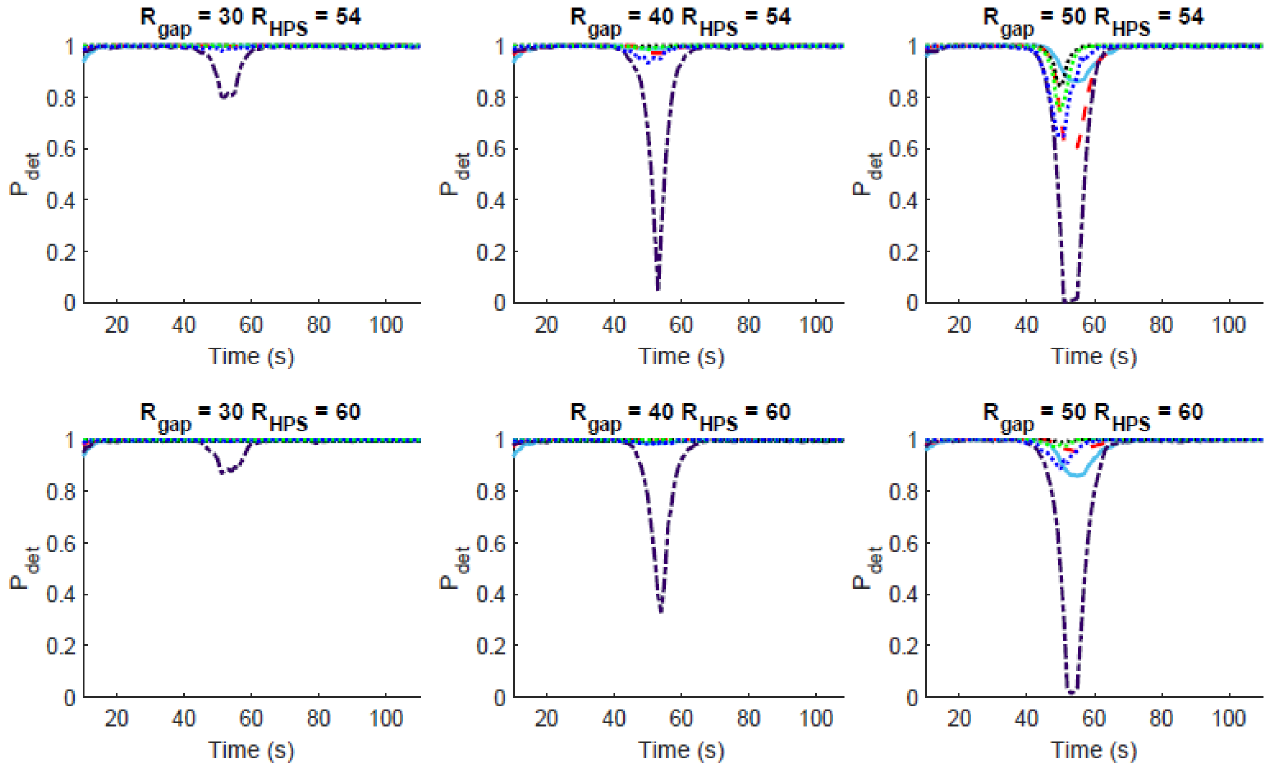
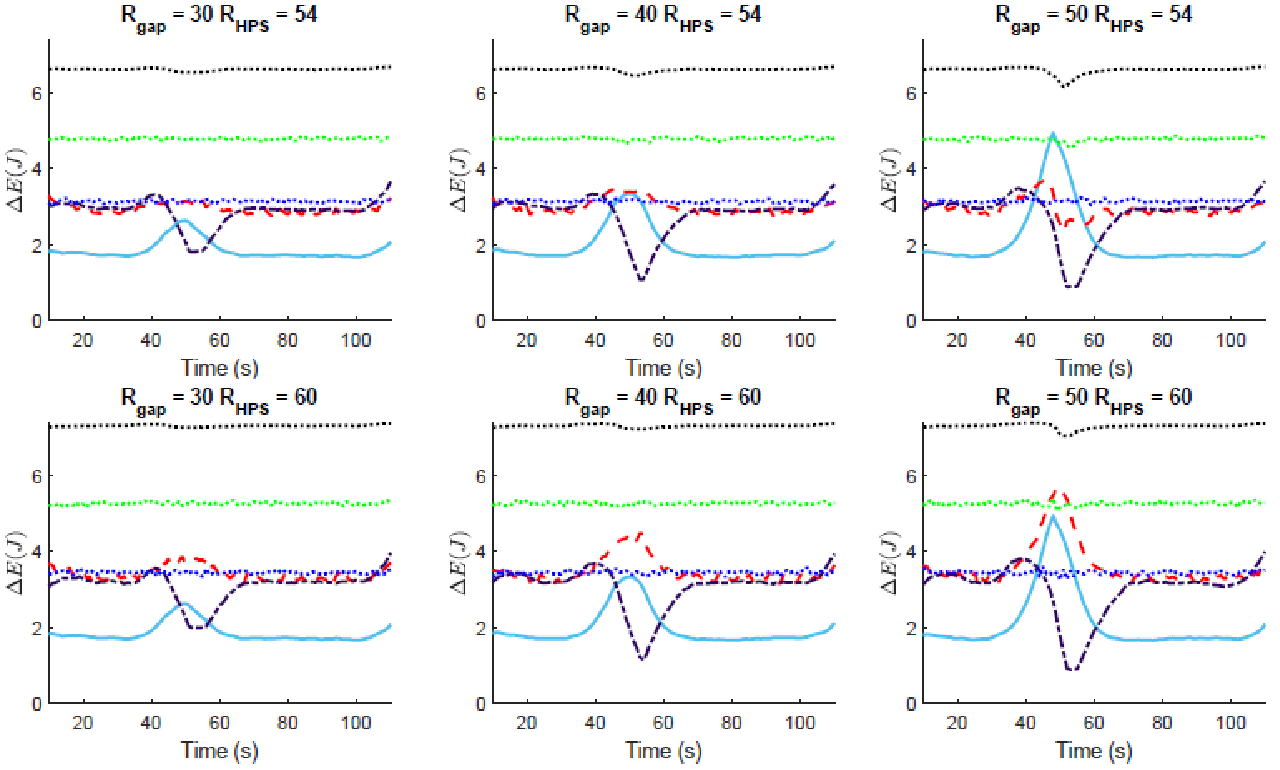


Average Energy Consumption w/in $60m$ of the targets position vs. Time



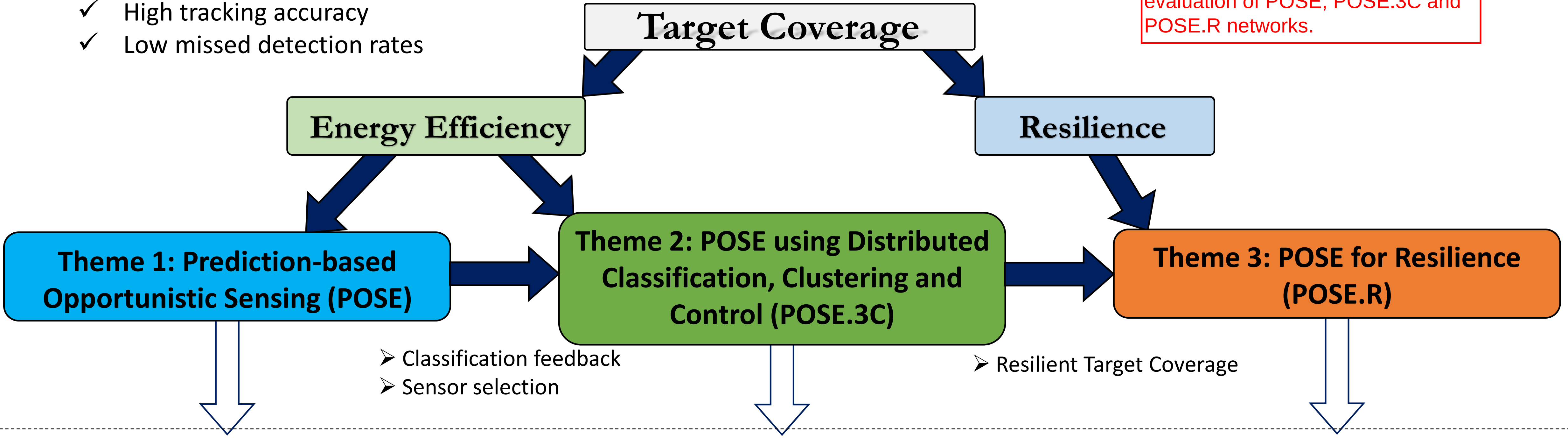
POSE.R, $p_{sleep} = 0.5$ — ANS — LPS-HPS — RAND, $p_{rand} = 0$ — RAND, $p_{rand} = 0.25$ — RAND, $p_{rand} = 0.5$

Conclusion

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

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



- ❑ 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

Novel Contributions

Publications

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- J. Z. Hare, S. Gupta and J. Wilson, "Decentralized Smart Sensor Scheduling for Multiple Target Tracking for Border Surveillance", *IEEE International Conference on Robotics and Automation*, Seattle, WA, May, (2015).
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- J. Song, S. Gupta and J. Z. Hare, "Game-theoretic Cooperative Coverage using Autonomous Vehicles", *Proceedings of OCEANS'14 MTS/IEEE*, St. John's, Newfoundland, Canada, September, (2014).
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- J. Z. Hare, N. Najjar, S. Gupta, "System Level Fault Diagnosis on Aerospace Air Management Systems," Patent 14/687, 112, April 15, 2015.
- N. Najjar, J. Z. Hare, S. Gupta, "Optimal Sensor Selection and Fusion for Heat Exchanger Fouling Diagnosis in Aerospace Systems," Patent 14/700, 769, April 30, 2015.