LISC

LABORATORY FOR INTELLIGENT SYSTEMS AND CONTROLS

An Information Potential Approach for Tracking and Surveilling Multiple Moving Targets using Mobile Sensor Agents

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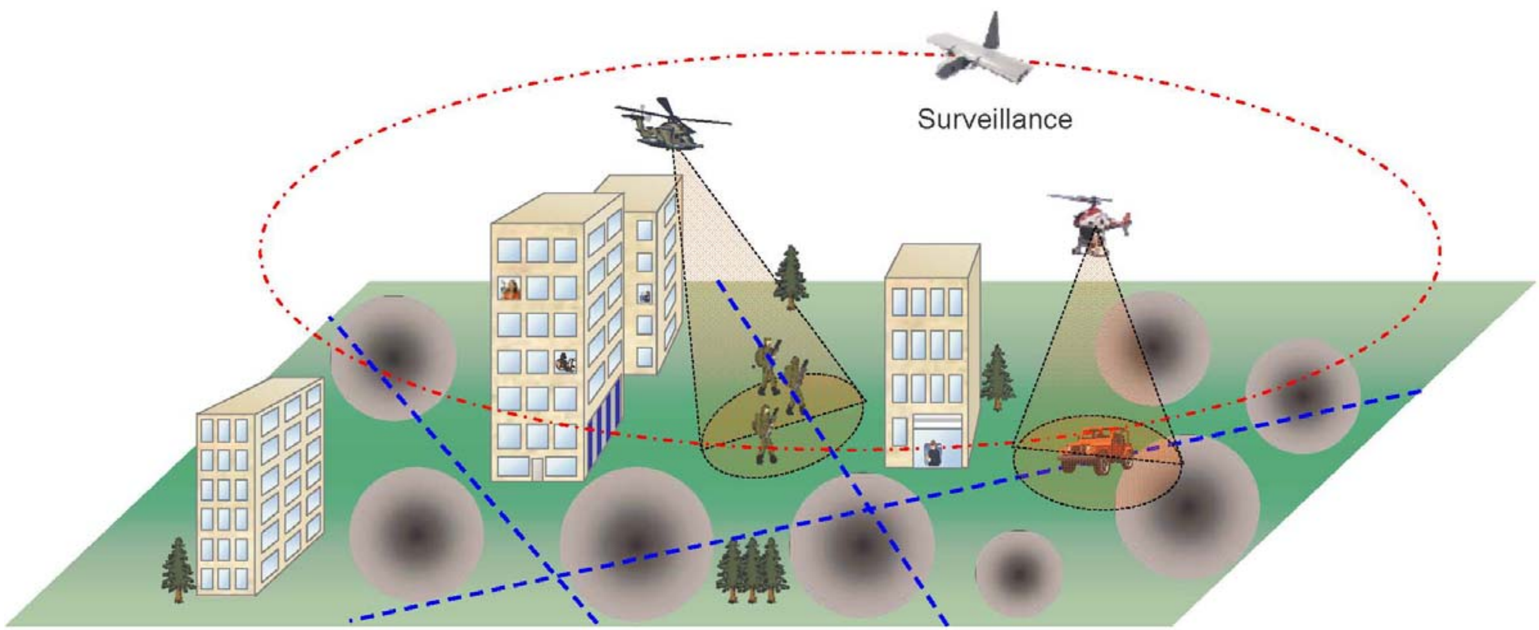
Introduction and Motivation

➢ Research Objectives

-- Online motion planning and control for mobile sensor agents (MSAs)

-- MSA Objectives: target tracking and surveillance; minimize energy consumption (e.g. distance traveled); and, avoid obstacles.

❖ Applications: Modern Surveillance Systems



Modeling of Targets and Mobile Sensors

Modeling of Target Dynamics

- Target state: $\mathbf{X}(t_k) = [\mathbf{x}(t_k) \quad \theta(t_k)]^T, \quad \mathbf{x}(t_k) = [x(t_k) \quad y(t_k)]^T$

- Markov motion process:

$$\dot{\mathbf{x}}(t) = v(t_k)[\cos\theta(t_k)\ \sin\theta(t_k)]^T, \quad \text{for} \quad t_k < t < t_{k+1}, \quad \text{where:}$$

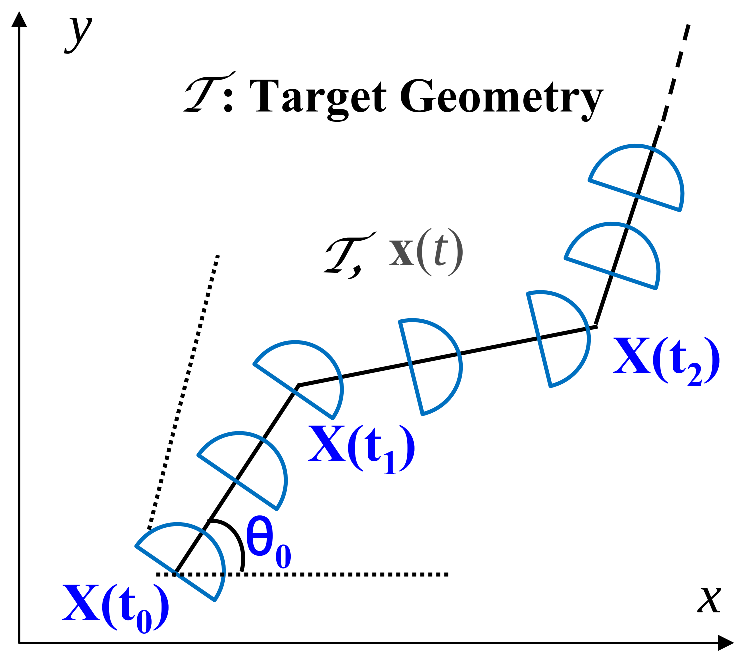
State transition at discontinuities:

$$\mathbf{X}(t_{k+1}) = \mathbf{X}(t_k) + \begin{bmatrix} \cos\theta(t_k)\tau v \\ \sin\theta(t_k)\tau v \\ N(\mu, \sigma^2) \end{bmatrix}$$

Target transition probabilities,

$$\Pr(\mathbf{x}(t_k), v(t_k), \theta(t_k)), \ k = 1, 2 \ldots,$$

are computed from sensor measurements.

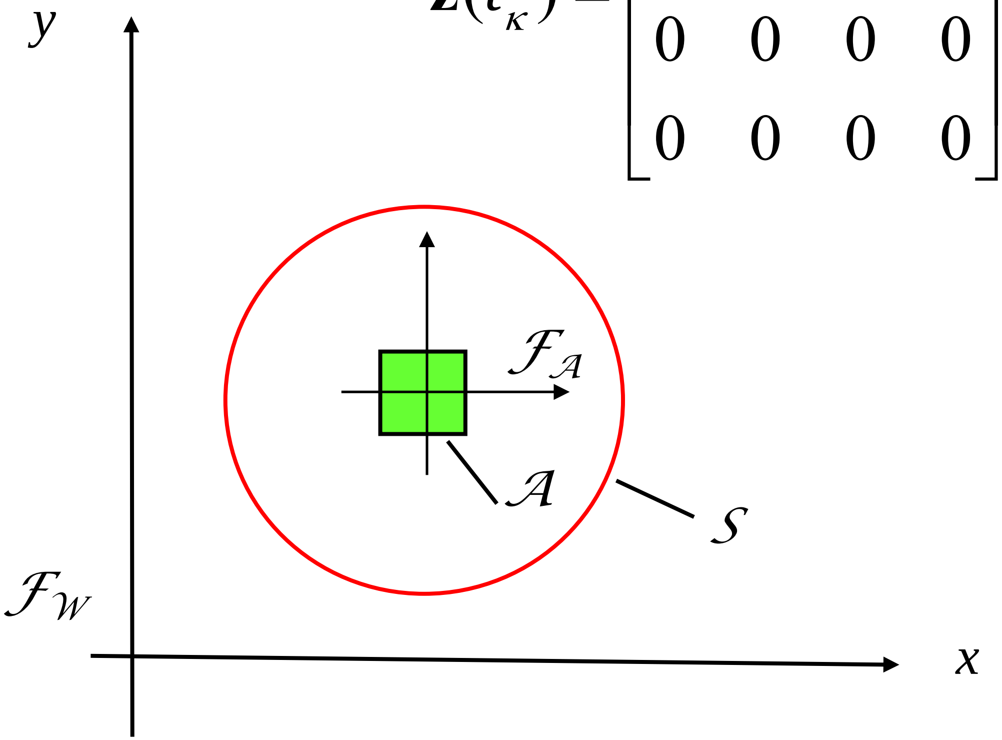


Model of Mobile Sensor Agent (MSA)

The sensor is characterized by a field-of-view (FOV) with geometry $\mathcal{S}$, and by a platform with geometry $\mathcal{A}$.
When the $\mathcal{S} \cap \mathcal{T} \neq \emptyset$, measurements are obtained according to equation:

$$\mathbf{z}(t_\kappa) = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \mathbf{x}(t_\kappa) + \boldsymbol{\upsilon}(t_\kappa)$$

white-noise error



Geometries:
Sensor FOV, $\mathcal{S}$
Sensor Platform, $\mathcal{A}$

Frames of reference:
Body frame, $\mathcal{F}_\mathcal{A}$
Inertial frame, $\mathcal{F}_W$

Model of MSA's Dynamics

The sensor position and velocity in $\mathcal{F}_{\mathcal{W}}$ are described by the vector,

$$\mathbf{y}(t_\kappa) = [x(t_\kappa)\ y(t_\kappa)\ \dot{x}(t_\kappa)\ \dot{y}(t_\kappa)]^T$$

and the platform dynamics are assumed to be LTI, and discretized w.r.t. time:

$$\mathbf{y}(t_\kappa) = \begin{bmatrix} 1 & 0 & \tau & 0 \\ 0 & 1 & 0 & \tau \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \mathbf{y}(t_{\kappa-1}) + \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ \tau & 0 \\ 0 & \tau \end{bmatrix} \mathbf{u}(t_{\kappa-1})$$

Where, $\mathbf{u}(t_\kappa)$ is the sensor's platform feedback control input vector.

Sensor Objectives:
Target Tracking and Surveillance

Target Tracking: Particle Filter Method

The particle filter is a recursive method to estimate a probability density function (PDF), e.g. $f(\theta(t_\kappa) \mid \mathbf{z}(t_{0\to\kappa}))$, based on sequential Monte Carlo simulations.

- Each iteration has three steps
  - Sampling particles from an importance density function (IPD): $q(\theta)$
  - Update the weight for each particle using Bayes' rule:

$$w_p \propto \frac{f(\theta(t_\kappa) \mid \mathbf{z}(t_{0\to\kappa}))}{q(\theta_p)},$$

$$f(\theta_p \mid \mathbf{z}(t_{0\to\kappa})) \propto f(\mathbf{z}(t_\kappa) \mid \theta_p, \mathbf{z}(t_{0\to\kappa-1})) \times f(\theta_p \mid \mathbf{z}(t_{0\to\kappa-1}))$$

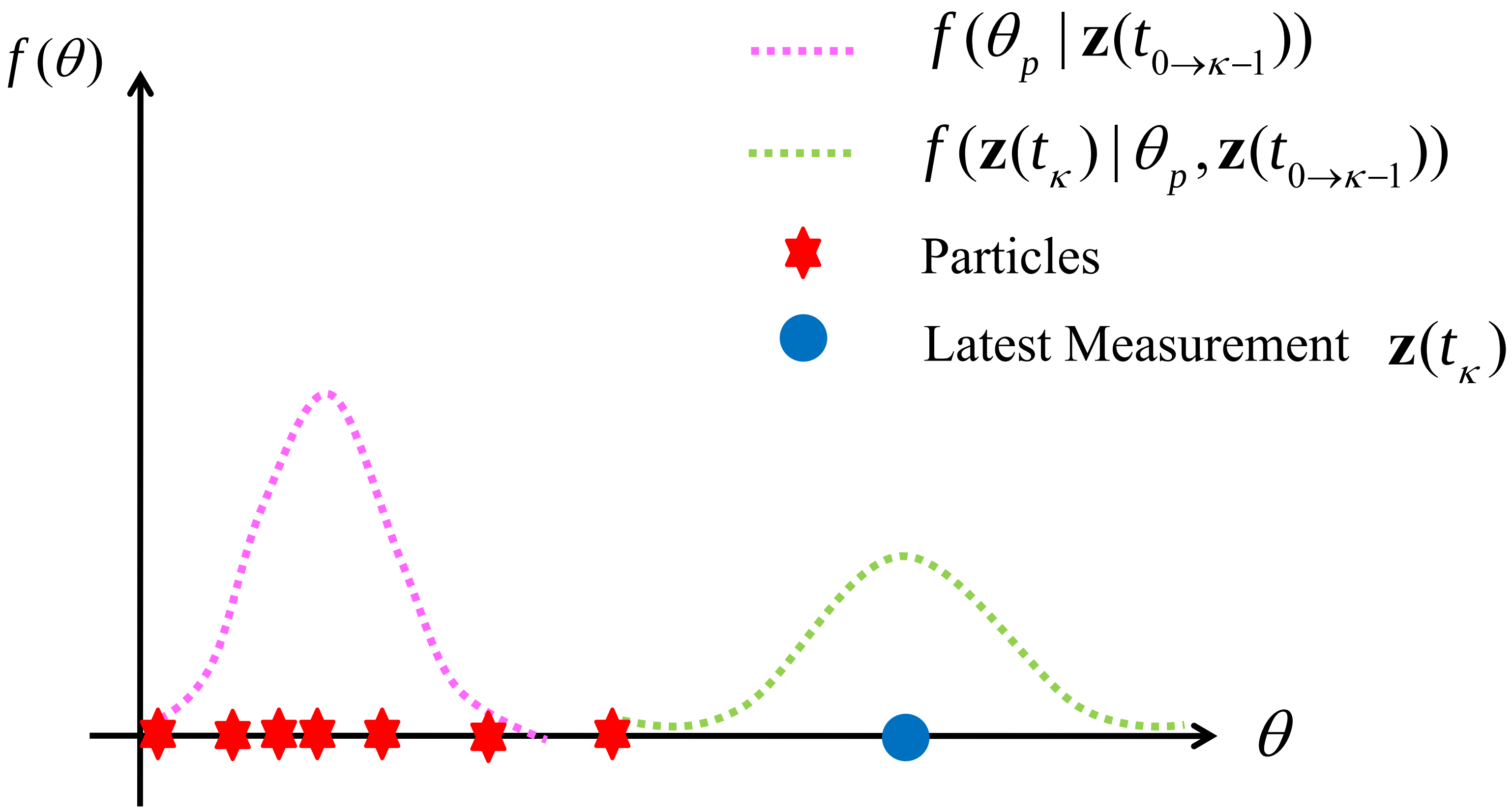
  - Re-sampling if effective size N_e is smaller than $\frac{N}{2}$

$$N_e = \frac{1}{\sum_{p=1}^{N} w_p^2}$$

- PDF representation: $\sum_{p=1}^{N} w_p \delta(\theta_p), \quad \sum_{p=1}^{N} w_p = 1, \quad w_p > 0$

Target Tracking: Particle Filter Update

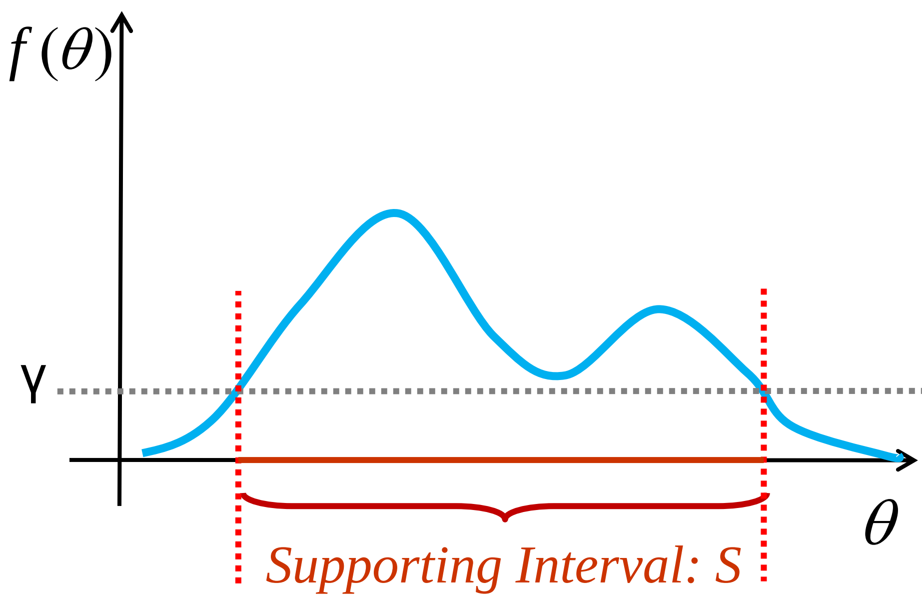
Particle filter method applied to target heading (θ) estimation:



Importance Probability Density Function

Definition of important probability density (IPD) function:

$$f_s(\theta) = \begin{cases} \frac{1}{L} & \text{if } \theta \in S \\ 0 & \text{else} \end{cases} \qquad L = \int_R g(\theta)d\theta \qquad g(\theta) = \begin{cases} 1 & \text{if } \theta \in S \\ 0 & \text{else} \end{cases}$$

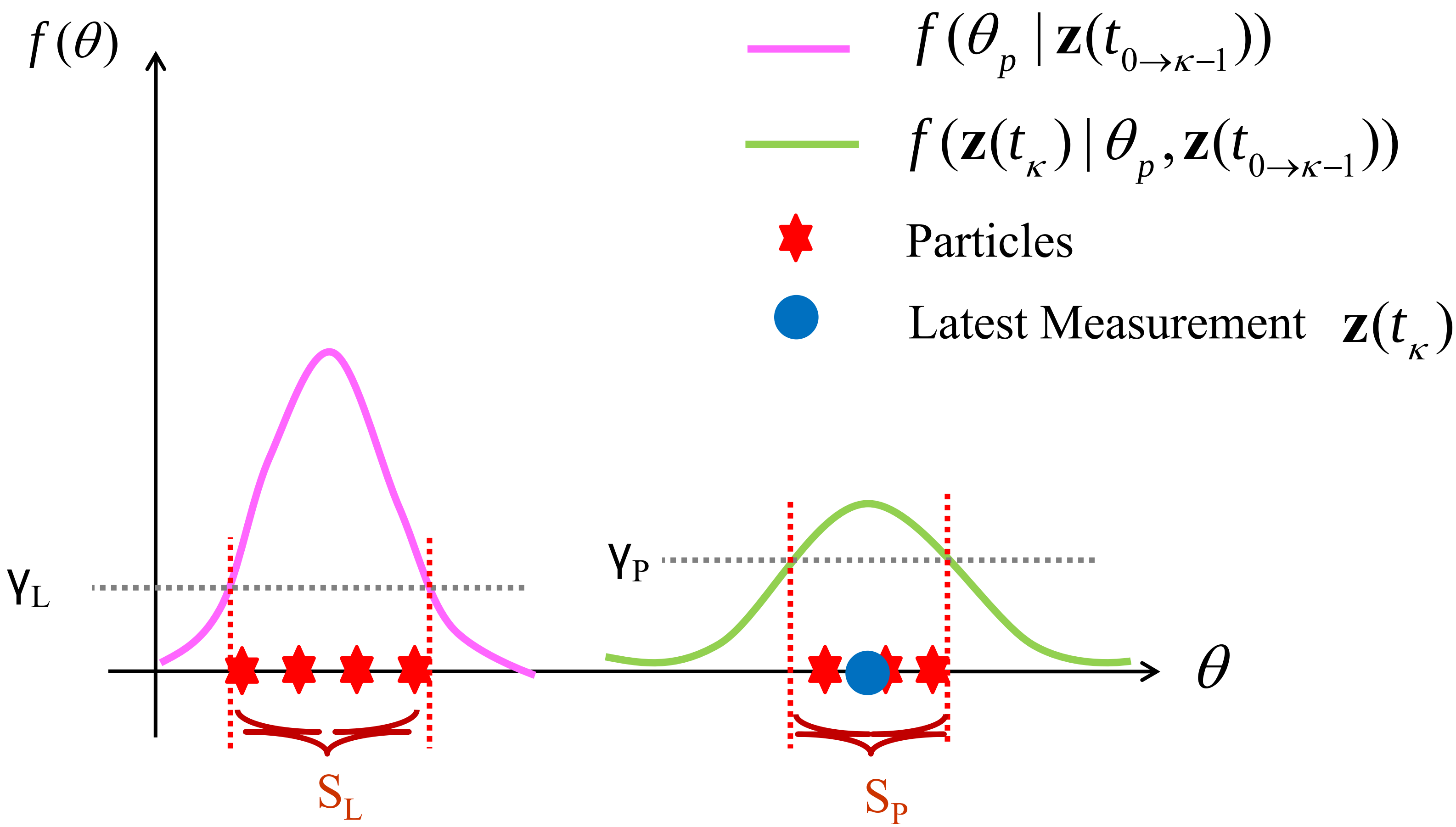


Approximate $f_S(\theta)$ by a finite mixture of Gaussians, $\sum_{i=1}^{m} \pi_i N(\mathbf{u}_i, \sigma_i^2)$, i.e.:

$$S_i : \left\{ \theta \,\middle|\, N\left(\theta \mid \mathbf{u}_i, \sigma_i^2\right) > \frac{\gamma}{\pi_i} \right\}$$

$$S = S_1 \cup S_2 \ldots \cup S_m$$

Particle Filter Update by Proposed IPD



$$S = S_L \cup S_P$$

Gaussian-Mixture Representation

- **Particle filter representation:** $\sum_{p=1}^{N} w_p \delta(\theta_p), \quad \sum_{p=1}^{N} w_p = 1, \quad w_p > 0$

⇩

- **Degeneracy phenomenon:** The variance of particle weight accumulates along iterations

⇩

- **Consequence:** A number of particles have low weights and no contributions in approximating

⇩

- **Re-sampling method:** The particles with high weights are repeated, redundant particles

- **Gaussian Mixture:** $\sum_{i=1}^{m} \pi_i \, \mathrm{N}(u_i, \sigma_i^2)$

Information Potential Field Method

❖ **Classical Potential Field Method for Robot Navigation and Control:**

$$U(\mathbf{q}) = U_{att}(\mathbf{q}) + U_{rep}(\mathbf{q})$$

$$\mathbf{F} \propto -\nabla U(\mathbf{q})$$

❑ **Information Potential Field Method for MSA Navigation:**

$$U(\mathbf{q}) = \begin{cases} \frac{1}{2}\eta_t\left(\frac{1}{\rho(\mathbf{q_t},\mathbf{q})} - \frac{1}{\rho_0}\right)^2 & \text{if } \rho(\mathbf{q_t},\mathbf{q}) \leq \rho_0 \\ 0 & \text{if } \rho_0 < \rho(\mathbf{q_t},\mathbf{q}) < \rho_1 \\ \frac{1}{2}\xi_t(\rho(\mathbf{q}^*,\mathbf{q}) - \rho_1)^2 & \text{if } \rho(\mathbf{q_t},\mathbf{q}) \geq \rho_1 \end{cases}$$

$$\mathbf{q}^* = \mathbf{q}_t + \alpha \begin{bmatrix} \cos\tilde{\theta}^s \\ \sin\tilde{\theta}^s \end{bmatrix} (\rho(\mathbf{q}_t,\mathbf{q}_s) - \rho_1)$$

❑ **Information Potential Field (IPF) - MSA Control Law:**

$$\mathbf{u}(\mathbf{q}) = v\begin{bmatrix} \cos\tilde{\theta}(t_\kappa) \\ \sin\tilde{\theta}(t_\kappa) \end{bmatrix} - \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}\mathbf{y}(t_\kappa) - \nabla U(\mathbf{q})$$

Stability of IPF Control Law

❖ Proposed Lyapunov Function for IPF Control:

Wenjie: Please write on this slide the proof and eq. (30)-(31) from the paper.

Simulations and Results

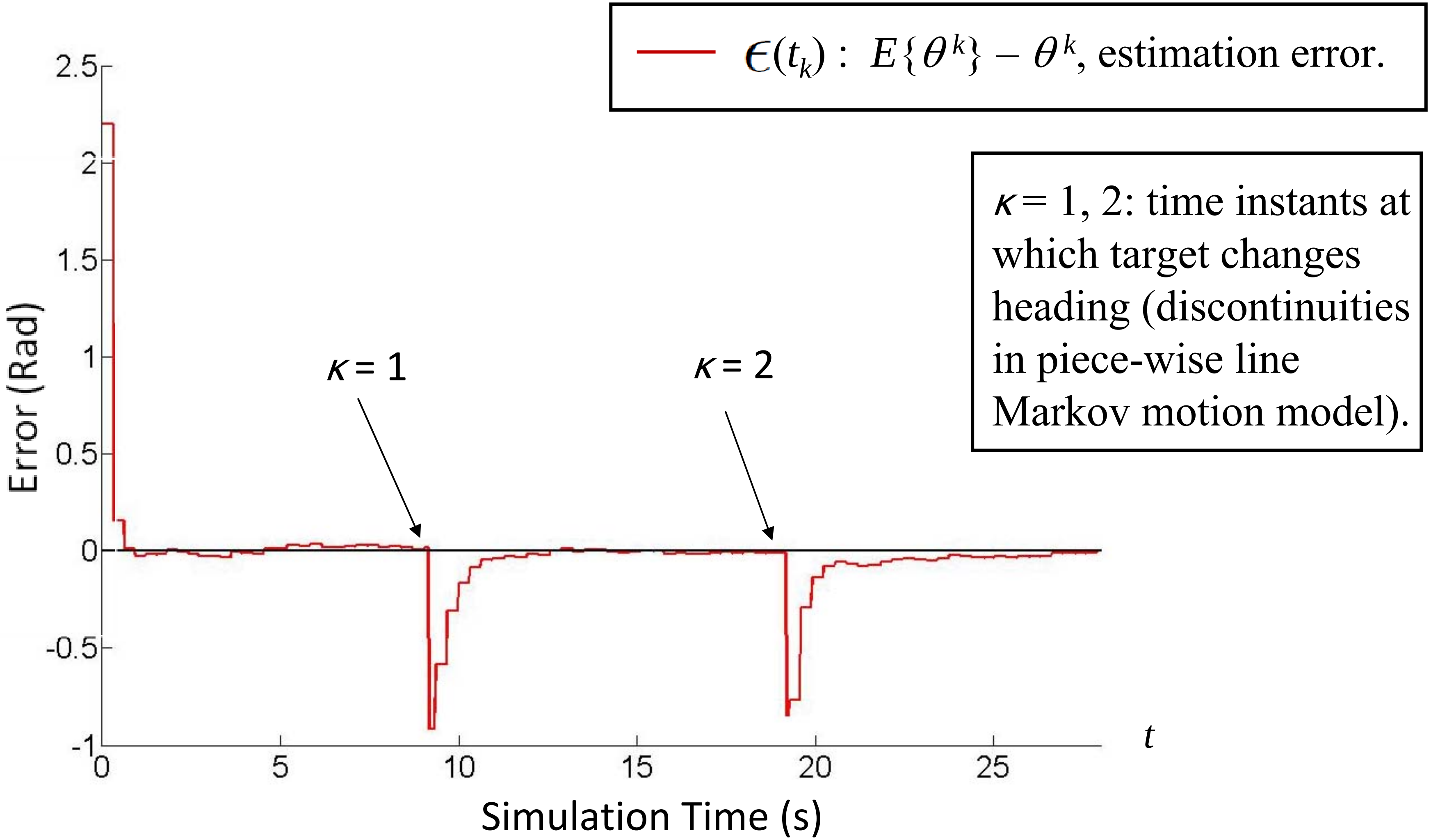
Simulated Scenario # 1

Scenario: The sensor platform and the target are modeled as point masses, the workspace has no obstacles

Simulation parameters:

Parameter	Value
Target speed (v)	2m/s
Workspace size	50m×50m
Heading changing frequency	0.1Hz
Measuring frequency	3.3Hz
Measuring noise	diag (0.4 0.4)

Results: Particle-Filter Target Tracking



$\kappa = 1, 2$: time instants at which target changes heading (discontinuities in piece-wise line Markov motion model).

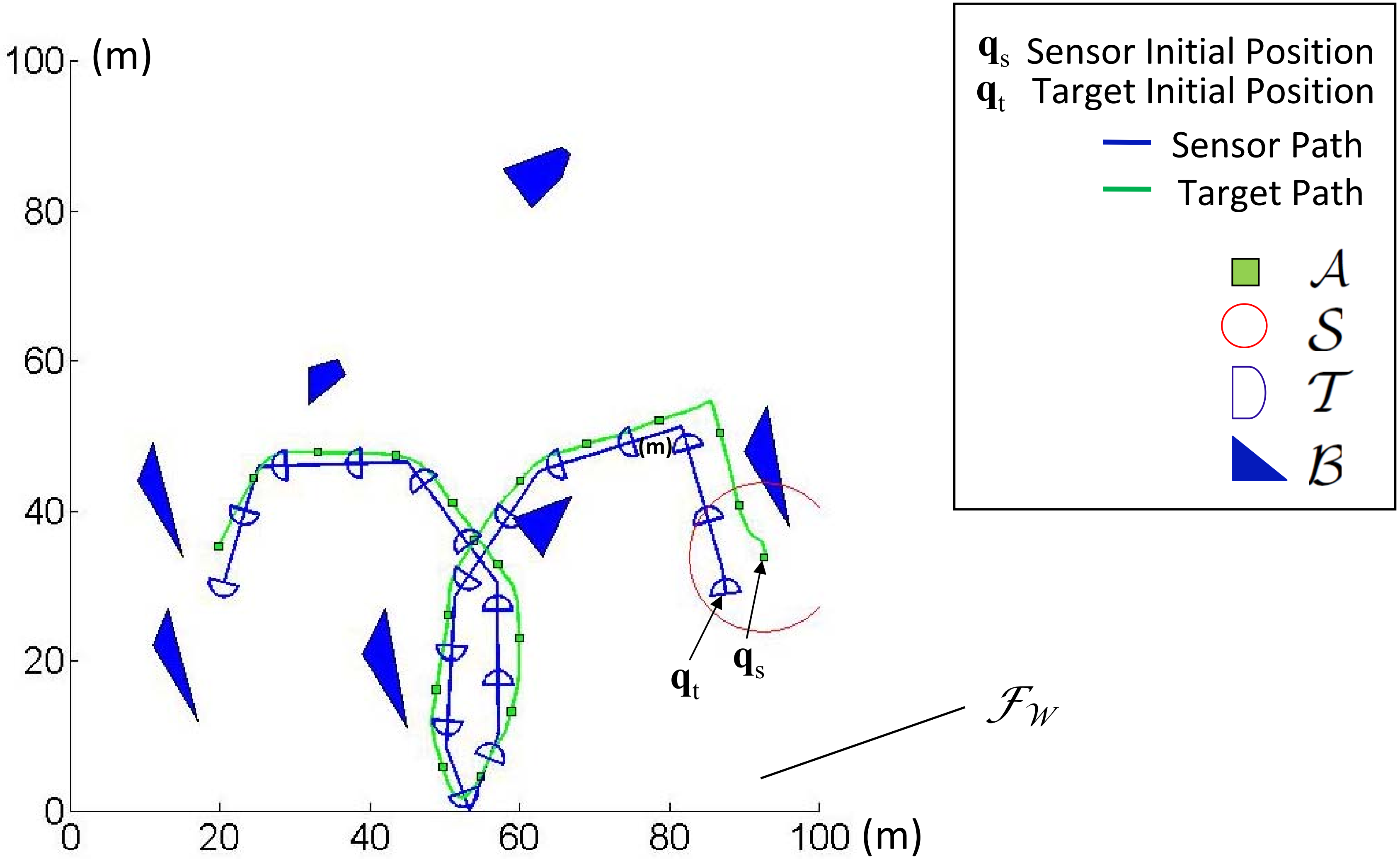
Simulated Scenario # 2

Scenario: The workspace is populated with 7 obstacles; the target and the sensor's platform have finite geometries (bdd subsets of R^2).

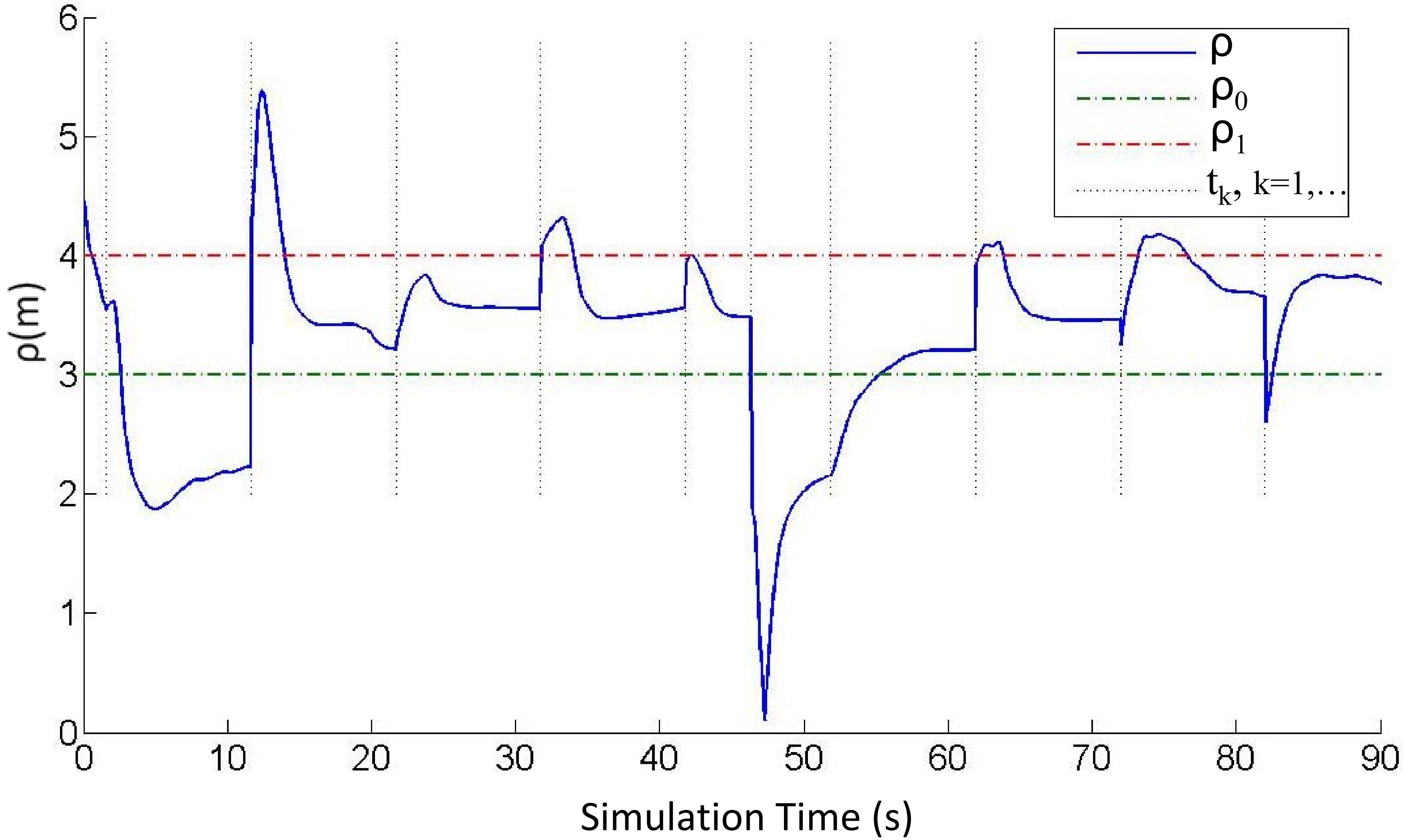
Simulation parameters:

Parameter	Value
Target speed (v)	2m/s
Workspace size	100m×100m
Heading changing frequency	0.1Hz
Measuring frequency	3.3Hz
Measuring noise	diag (0.4 0.4)
ρ_0	3m
ρ_1	4m

Results: Sensor Path Planning



Results: Sensor Surveillance



Summary and Conclusions

Results:

- Integration of geometric target and sensor modeling
- Particle filter method for target tracking
- Information potential field method:
  sensor path planning for tracking and surveillance

Future work:

- Estimate multiple Markov parameters (e.g. speed)
- Adaptive dynamic programming (ADP) approach
- Experimental testing

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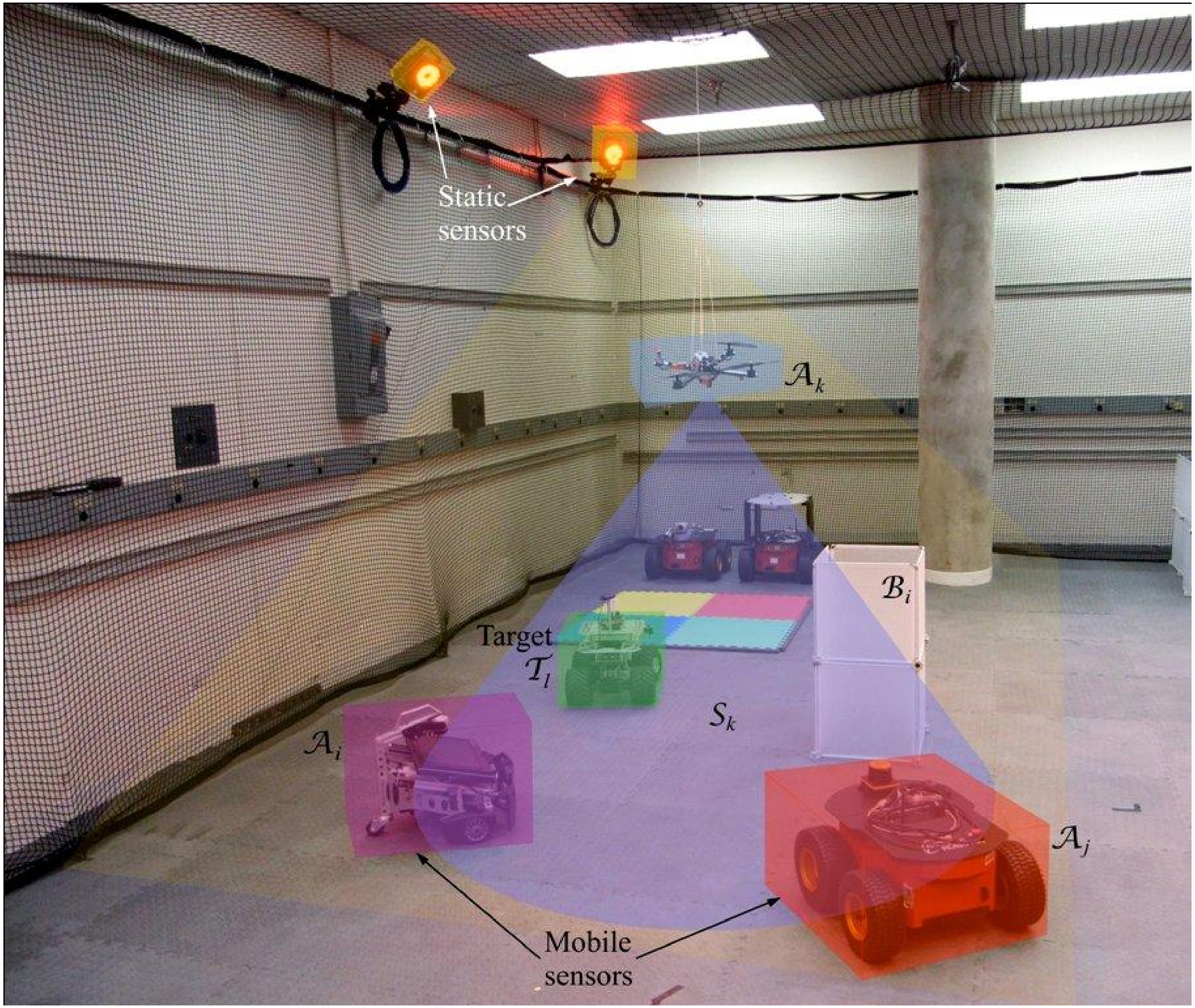
Future Work: MARHES Experimental Testbed



Experimental Testing Concept