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LABORATORY FOR INTELLIGENT SYSTEMS AND CONTROLS

Information Driven Path Planning and Control for Collaborative Aerial Robotic Sensor Using Artificial Potential Functions

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Outline

- Introduction and Motivation
- Problem Formulation : Aerial Robotic Sensor Path Planning
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- Results
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  - Multiple Sensors
- Conclusion and Recommendations

Introduction and Motivation

- Modern Sensor Systems – multiple sensors installed on mobile platforms

  - landmine detection and identification

  - ambient intelligence, monitoring of urban environments, search & rescue

- Traditional paradigm: sensor information is used as feedback to sensors in order to support the sensor navigation.

- New paradigm: sensors' motion is planned considering the expected utility of future measurement process, to support one or more sensing objectives

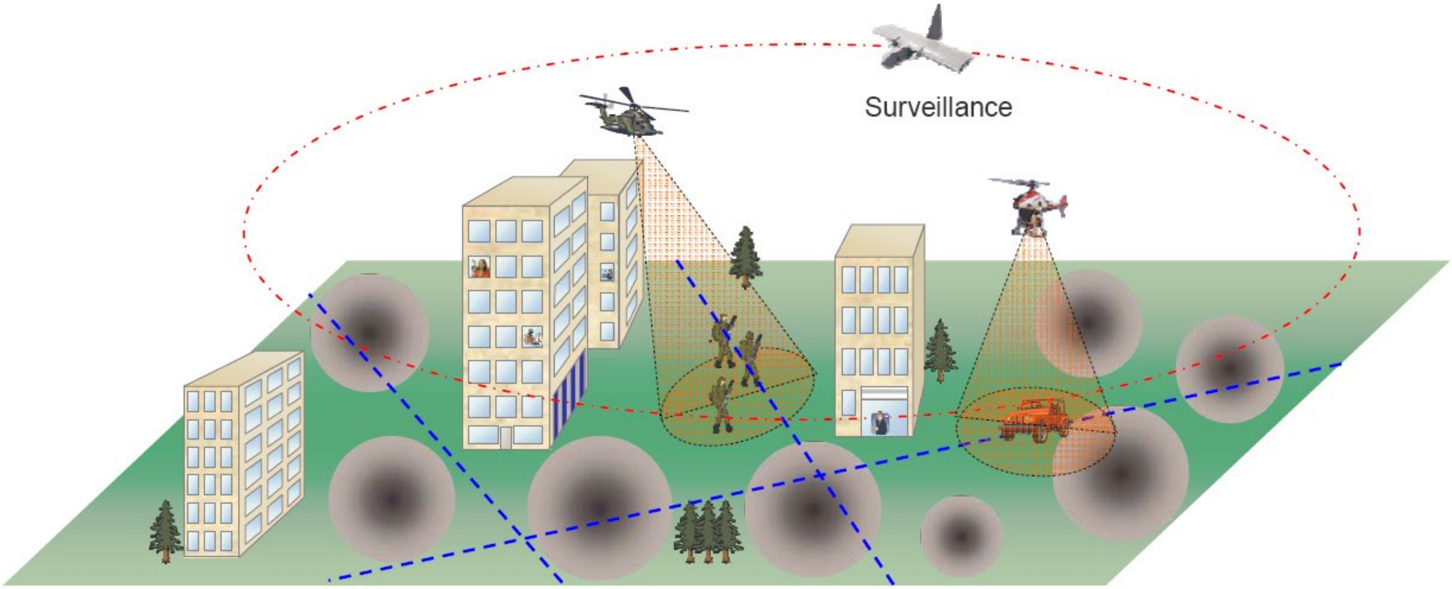
- **Research Emphasis:** Geometric aerial robotic sensor path planning

  -- Address couplings between sensor measurements and sensor dynamics

  -- Optimize sensing objectives (e.g., detection, classification, tracking.)

Motivation: Applications of Sensor Path Planning

- Applications: landmine detection, sensor networks for monitoring endangered species



M. Qian and S. Ferrari, "Probabilistic deployment for multiple sensor systems," Proc. SPIE, 2005

C. Cai and S. Ferrari, "Information-Driven Sensor Path Planning by Approximate Cell Decomposition," IEEE Transactions on Systems, Man, and Cybernetics - Part B, Vol. 39, No. 2, 2009.

Problem Formulation

Problem Formulation: Aerial Robotic Sensor Path Planning

Given workpace $\mathcal{W} \subset \mathbb{R}^3$, where r robotic sensor plaftorms $A = \{\mathcal{A}_1, \cdots, \mathcal{A}_r\} \subset \mathcal{W}$ with sensor FOV $S = \{\mathcal{S}_1, \cdots, \mathcal{S}_r\} \subset \mathcal{W}$, n fixed obstacles $B = \{\mathcal{B}_1, \cdots, \mathcal{B}_n\} \subset \mathcal{W}$ m fixed targets $T = \{\mathcal{T}_1, \cdots, \mathcal{T}_m\} \subset \mathcal{W}$

State $\mathbf{q}_i = [x_i \; y_i \; z_i \; \theta_i]^T$

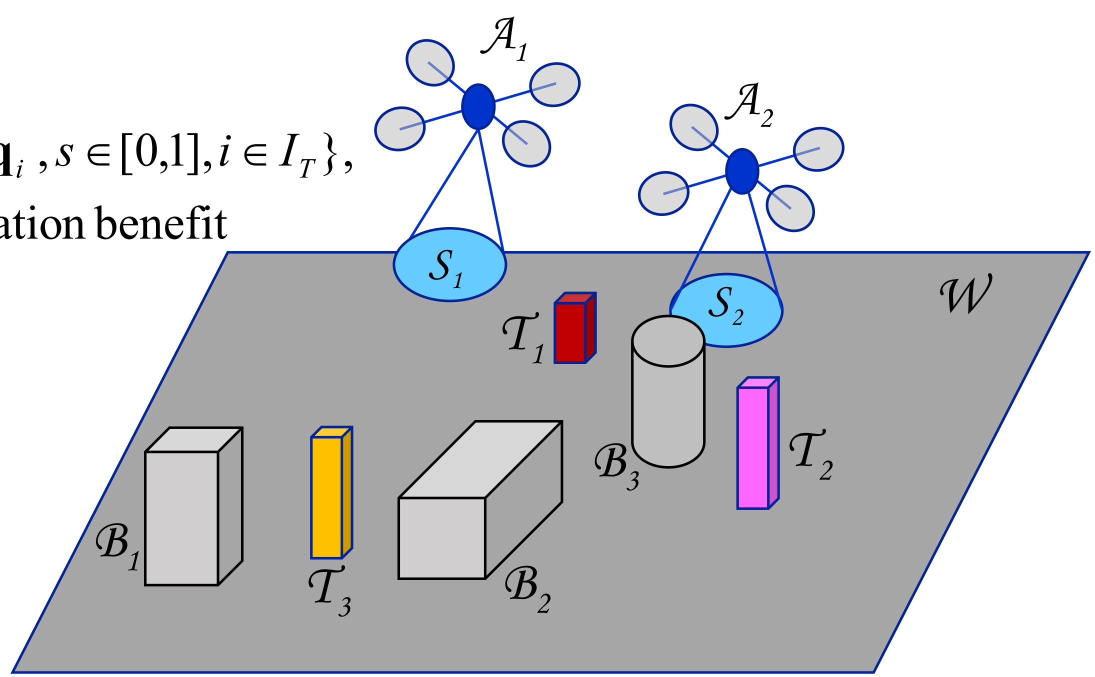
Purpose:

Find a sequence of measurements

$Z(\tau) = \{Z_i \mid \mathcal{T}_i \cap \mathcal{S}(\mathbf{q}_i) \neq \phi, \tau(s) = \mathbf{q}_i, s \in [0,1], i \in I_T\}$,

to optimize some expexted observation benefit

$$V[Z(\tau)] = \sum_{Z_i \in Z(\tau)} V(Z_i).$$



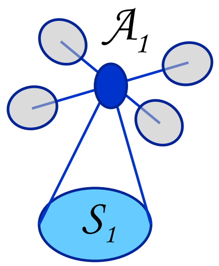
Problem Formulation: Aerial Robotic Sensor Dynamics

- Motion dynamics

$$M\ddot{\mathbf{P}} = -\mu_f \mathbf{R}\mathbf{e}_3 + Mg\mathbf{e}_3$$

$$\dot{\mathbf{R}} = \mathbf{R}\mathbf{S}(\mathbf{w})$$

$$\mathbf{J}\dot{\mathbf{w}} = \mathbf{S}(\mathbf{J}\mathbf{w})\mathbf{w} + \boldsymbol{\mu}_\tau$$



$$\mathbf{P} = [x_i\ y_i\ z_i]$$

$$\mathbf{w} = [\mathbf{w}_x\ \ \mathbf{w}_y\ \ \mathbf{w}_z]$$

$$\mathbf{e_3} = [\,\mathbf{0}\ \ \mathbf{0}\ \ \mathbf{1}]^T$$

$$\boldsymbol{S}(\ [x_1\ x_2\ x_3]^T\ ) = \begin{bmatrix} 0 & -x_3 & x_2 \\ x_3 & 0 & -x_1 \\ -x_2 & x_1 & 0 \end{bmatrix}$$

$\mathbf{P} \in \mathbb{R}^3$: position of center gravity

$\mathbf{w} \in \mathbb{R}^3$: angular speed (body frame)

$\mathbf{R} \in \mathbb{R}^{3\times 3}$: rotation matrix(body$\rightarrow$inertial)

$M \in \mathbb{R}_{>0}$: mass

$\mathbf{J} \in \mathbb{R}^{3\times 3}$: inertia matrix

$\mu_f \in \mathbb{R}_{\geq 0}$: control force

$\boldsymbol{\mu}_\tau \in \mathbb{R}^3$: control torque vector

Methodology

Information Value

Entropy $H(X) = -\sum_{x \in X} p(x) \log p(x)$

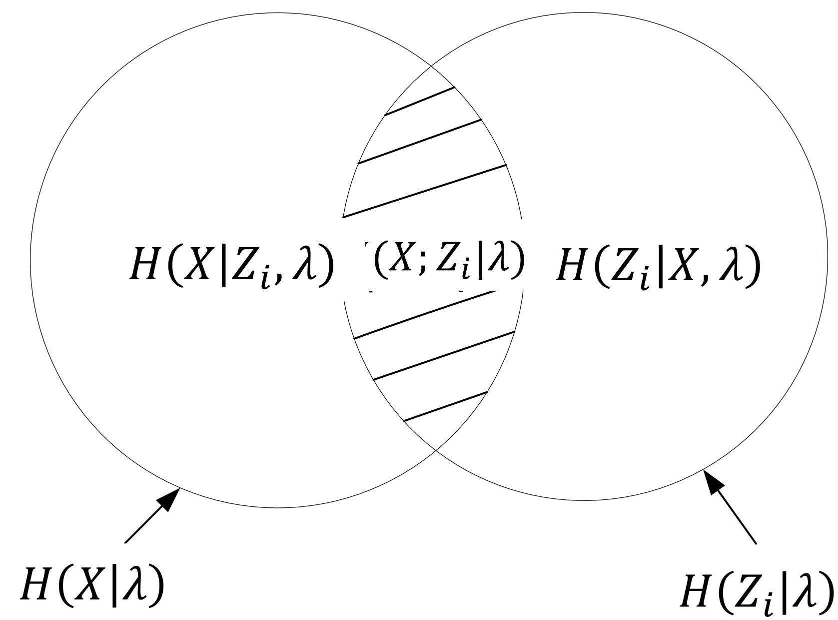
Conditional entropy $H(X|Z_i) = \sum_{z_i \in Z} p(z_i) H(X|z_i)$

Conditional mutual information

$$I(X; Z_i|\lambda) = H(X|\lambda) - H(X|Z_i, \lambda)$$

Information Benefit to have Z_i

$$V(Z_i) = I(X; Z_i|\lambda)$$



M. Cover and J. Thomas, Elements of Information Theory, 1991

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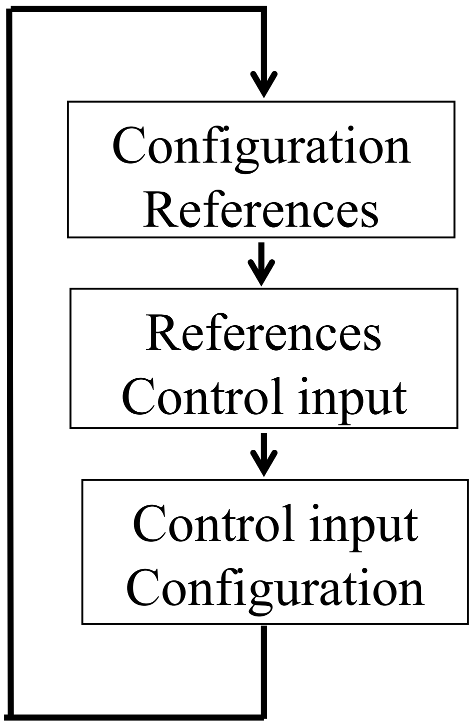
Hybrid Controller



Mode planner
High level controller

Information potential*

Low level
controller

Cascade control**

UAV simulator

W. Lu, G. Zhang, and S. Ferrari, “An Information Potential Approach to Integrated Sensor Path Planning and Control” IEEE Transaction on Robotics, to appear

***R. Naldi, M. Furci, “Global Trajectory Tracking for Underactuated VTOL Aerial Vehicles using a Cascade Control Paradigm”, IEEE Conference on Decision and Control, 2013*

Information Potential Field Construction

Potential at **q**

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

Novel attractive potential the *i*th target

$$U_i(\mathbf{q})_{att} = \eta_2 \sigma V_i^a \left(1 - e^{-\frac{\rho_i^t(\mathbf{q})^2}{2\sigma V_i^a}}\right)$$

Total attractive potential

$$U(\mathbf{q})_{att} = \prod_{i=1}^{m} U_i(\mathbf{q})_{att}$$

Repulsive potential of the *i*th obstacle

$$U_i(\mathbf{q})_{rep} = \begin{cases} \frac{1}{2}\eta_1 \left(\frac{1}{\rho_i^b(\mathbf{q})} - \frac{1}{\rho_0} \right)^2 U(\mathbf{q})_{att} & \text{if} \quad \rho_i^b(\mathbf{q}) \le \rho_0 \\ 0 & \text{if} \quad \rho_i^b(\mathbf{q}) > \rho_0 \end{cases}$$

Potential between two robotic sensors

$$U_{rk}^j(\mathbf{q}) = \begin{cases} \frac{1}{2}\eta_3 \left(\frac{1}{\rho_{jk}^r(\mathbf{q})} - \frac{1}{\rho_0} \right)^2 U(\mathbf{q})_{att} & \text{if} \quad \rho_{jk}^r(\mathbf{q}) \le \rho_0 \\ 0 & \text{if} \quad \rho_{jk}^r(\mathbf{q}) > \rho_0 \end{cases}$$

Total repulsive potential

$$U(\mathbf{q})_{rep} = \sum_{i=1}^{n} U_i(\mathbf{q})_{rep}$$

**W. Lu, G. Zhang, and S. Ferrari, "An Information Potential Approach to Integrated Sensor Path Planning and Control" IEEE Transaction on Robotics, to appear*

Connection Between IRD and Potential Field Methods

When the robotic sensor is at a local minimum, randomly generate milestones in surrounding subspace

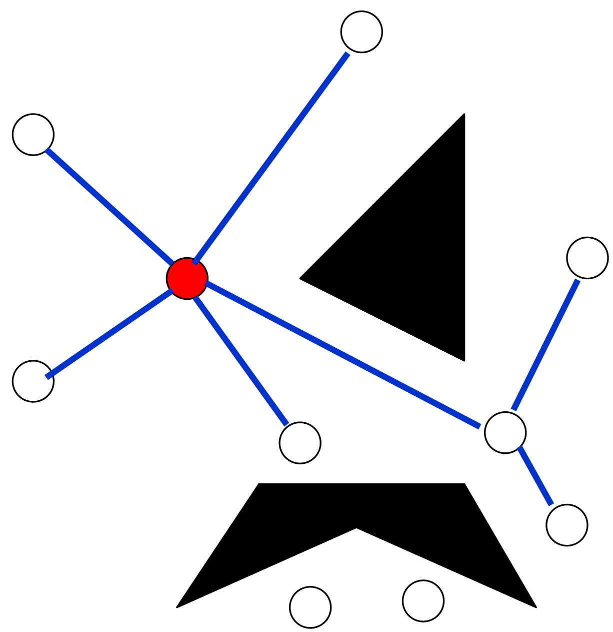
Milestones distribution

$$f(\mathbf{q}) = \begin{cases} \dfrac{e^{-U(\mathbf{q})}}{\int_A e^{-U(\mathbf{q})} d\mathbf{q}} & \text{if} \quad \mathbf{q} \in A \\ 0 & \text{if} \quad \mathbf{q} \notin A \end{cases}$$

A function of the potential at **q**, $e^{-U(\mathbf{q})}$, is used to measure the probability of sampling a milestone at **q**.

Escaping Local Minima by IRD method

The milestones are connected to the local minimum to construct the roadmap



A path from the local minimum to a milestone with lower potential than the potential at the local minimum is found.

High Level Control and Low Level Control

High Level Control:

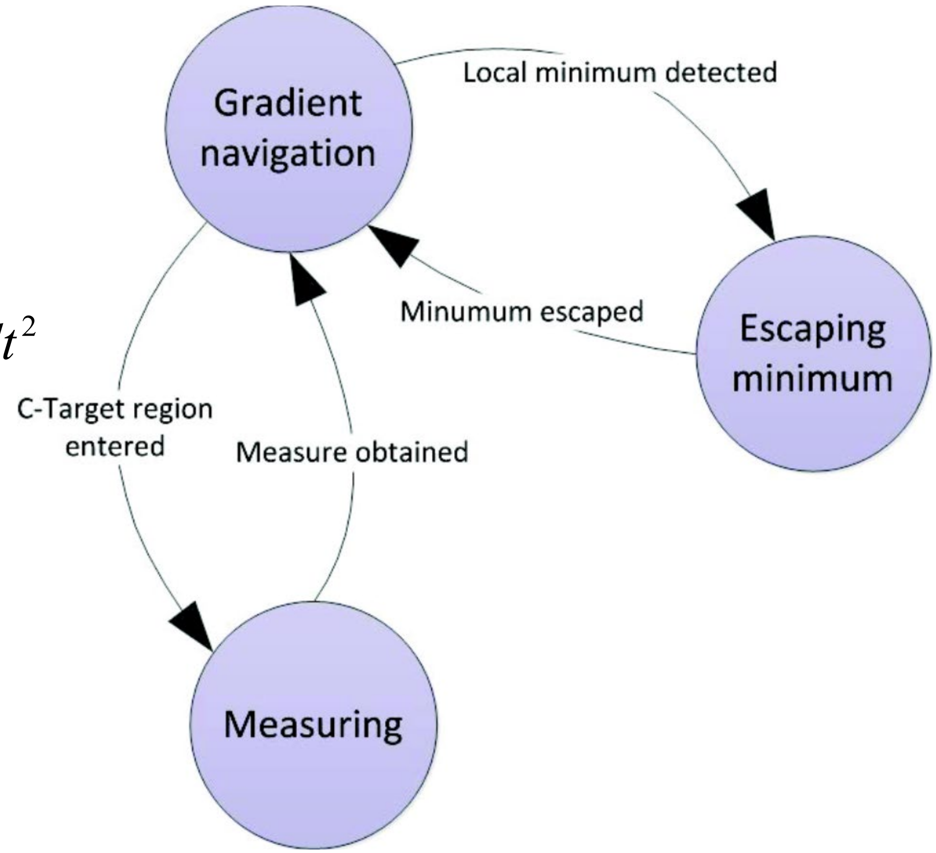
1. Fix time step as dt,

$$\mathbf{q}^r(t+dt) = \mathbf{q}_j(t) + \dot{\mathbf{q}}_j(t)dt$$

$$-\frac{1}{2}\nabla U_j(\mathbf{q}) \otimes \begin{bmatrix} \frac{1}{M} & \frac{1}{M} & \frac{1}{M} & \frac{1}{I} \end{bmatrix}^T dt^2$$

2. Information Potential

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



Low Level Cascade Control*:

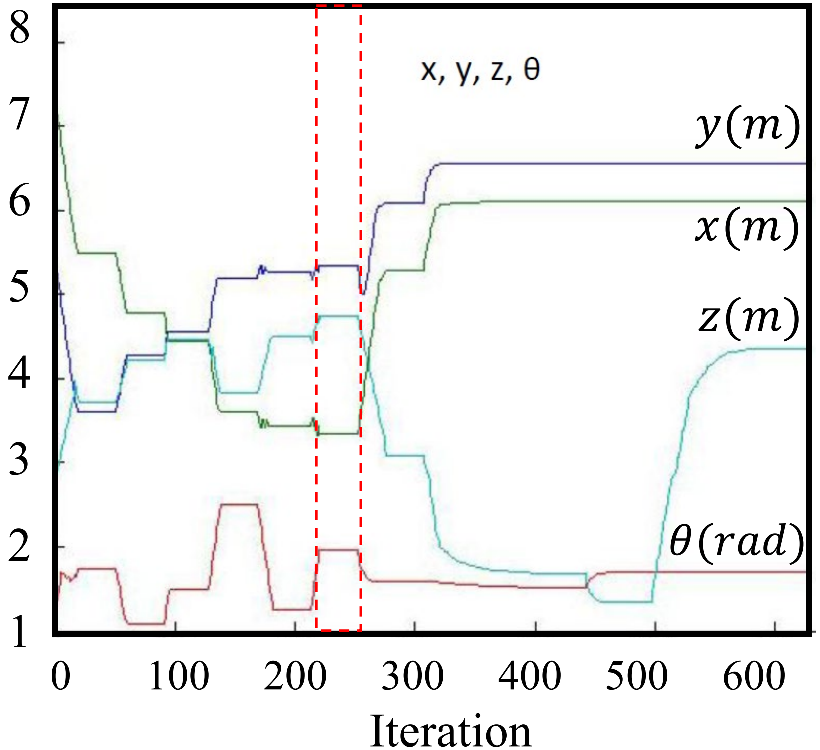
1. Position Control Law
2. Attitude Control Law

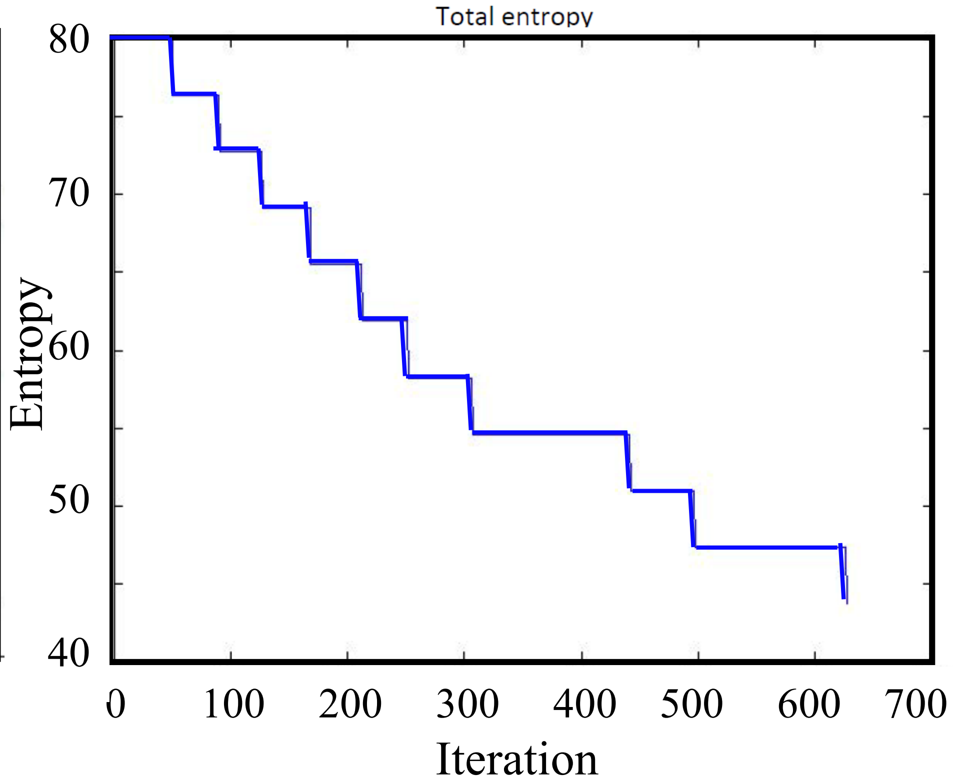
***R. Naldi, M. Furci, "Global Trajectory Tracking for Underactuated VTOL Aerial Vehicles using a Cascade Control Paradigm", IEEE Conference on Decision and Control, 2013**

Results

Result: One Sensor

One robotic sensor
n targets with same V_i
m fixed obstacles
r moving obstacles





Result: Two Sensors

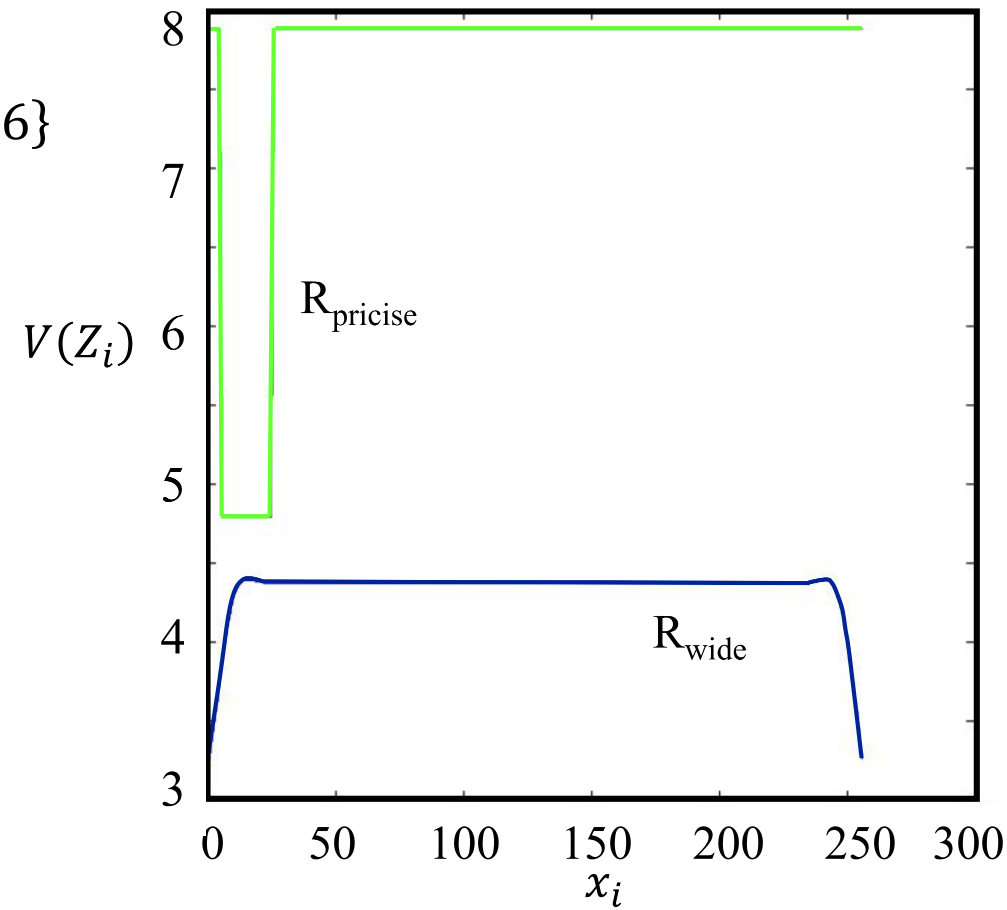
First sensor (R_{wide}): Range [1, 256], white Gaussian noise of $\sigma = 5$

Second sensor ($R_{precise}$): Range [5, 25], white Gaussian noise of $\sigma = 0.1$

One target:

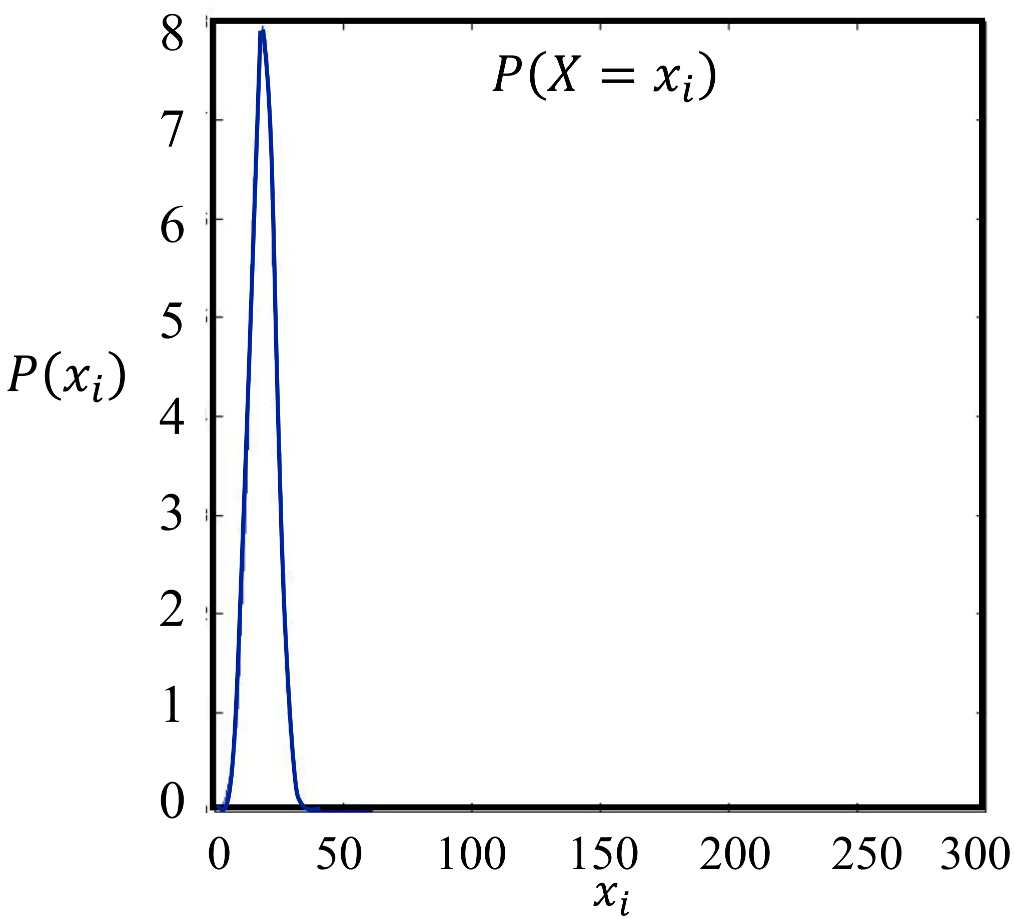
$$P(X = x_i) = \frac{1}{256}, x_i \in \{1,2,\cdots,256\}$$

$$V_{wide} = 3.67$$
$$V_{precise} = 0.35$$



Result: Two Sensors

After R_{wide} senses the target,



$$\boxed{V_{wide} = 0, \quad V_{precise} > 0}$$

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Conclusions

- Hybrid controller for aerial robotic sensor path planning
- Information potential and reference model are integrated to design high level controller
- Cascade controller navigates sensor along reference trajectories
- Maximizing classification performance.

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