Ph.D. Preliminary Exam

Cooperative Control of Mobile Sensors in Dynamic Environments

Shankarachary Ragi

Department of Electrical and Computer Engineering,
Colorado State University

Spring 2013

Mobile Sensor

- Senses the environment
- Communicates with other mobile sensors or a base station
- Runs computations
- Changes its state (the state of a mobile sensor may include, e.g., its sensing direction, location, and waveform)

(a) UAV with on-board sensors

(b) PTZ camera

Cooperative Control

- Defense and civilian applications—surveillance, tracking, wild-fire suppression
- Focus—developing planning methods to
  - control multiple unmanned aerial vehicles (UAVs) for tracking multiple targets
  - control multiple autonomous amphibious vehicles (AAVs) for flood rescue support
  - control directional sensors for maximizing information gain
- Frameworks:
  - Centralized system—POMDP
  - Decentralized system—Dec-POMDP

Centralized UAV Guidance for Tracking Multiple Targets

Publications

1. S. Ragi and E. K. P. Chong, "UAV guidance algorithms via partially observable Markov decision processes," Chapter 59 in *Handbook of Unmanned Aerial Vehicles*, Dordrecht, Netherlands: Springer Science+Business Media, 2013, to be published.
2. S. Ragi and E. K. P. Chong, "UAV path planning in a dynamic environment via partially observable Markov decision process," *IEEE Trans. Aerosp. Electron. Syst.*, to be published.
3. S. Ragi and E. K. P. Chong, "Dynamic UAV path planning for multitarget tracking," in *Proc. American Control Conf.*, Montreal, Canada, 2012, pp. 3845–3850.

Problem Description

- Targets move in 2-D
- UAVs fly at a constant altitude
- UAVs with onboard sensors send measurement frames to notional fusion node
- Fusion node:
  - Constructs tracks from measurements
  - Plans future motion of UAVs
  - Sends motion commands back to UAVs
- Objective: minimize mean-squared error of target estimates

Non-Myopic Dynamic Control

- The problem is inherently *dynamic*
  - Must exploit feedback
  - Poor control actions—regret at a future time
- Need non-myopic approach!
- POMDP: Partially Observable Markov Decision Process

POMDP Formulation

state: $x_k = (s_k, \chi_k, \xi_k, P_k)$

- sensor state s_k
- target state χ_k
- track state (ξ_k, P_k)

POMDP Formulation

$$\text{state:} \quad x_k = (s_k, \chi_k, \xi_k, P_k)$$

$$\text{measurement:} \quad z_k^{\chi} = h(\chi_k, s_k) + w_k, \quad w_k \sim \mathcal{N}(0, R_k(\chi_k, s_k))$$

$$z_k^{s} = s_k, \quad z_k^{\xi} = \xi_k, \quad z_k^{P} = P_k$$

POMDP Formulation

state: $x_k = (s_k, \chi_k, \xi_k, P_k)$

measurement: $z_k^{\chi} = h(\chi_k, s_k) + w_k, \quad w_k \sim \mathcal{N}(0, R_k(\chi_k, s_k))$

action: $u_k = (a_k, \phi_k)$

- forward acceleration a_k and bank angle ϕ_k
  $a_k \in [a_{\min}, a_{\max}]^{N_{\text{sens}}} \quad \phi_k \in [\phi_{\min}, \phi_{\max}]^{N_{\text{sens}}}$

POMDP Formulation

$$
\begin{aligned}
\text{state:} \quad & x_k = (s_k, \chi_k, \xi_k, P_k) \\
\text{measurement:} \quad & z_k^{\chi} = h(\chi_k, s_k) + w_k, \quad w_k \sim \mathcal{N}(0, R_k(\chi_k, s_k)) \\
\text{action:} \quad & u_k = (a_k, \phi_k) \\
\text{state transition:} \quad & x_{k+1} = T(x_k, u_k, v_k, w_{k+1}), \quad v_k \sim \mathcal{N}(0, Q_k)
\end{aligned}
$$

$$
\begin{aligned}
s_{k+1} &= \psi(s_k, u_k) \\
\chi_{k+1} &= f(\chi_k) + v_k \\
(\xi_{k+1}, P_{k+1}) &= \text{Kalman filter update of } (\xi_k, P_k) \\
&\qquad \text{based on observed } z_{k+1}
\end{aligned}
$$

POMDP Formulation

$$
\begin{aligned}
\text{state:} \quad & x_k = (s_k, \chi_k, \xi_k, P_k) \\
\text{measurement:} \quad & z_k^{\chi} = h(\chi_k, s_k) + w_k, \quad w_k \sim \mathcal{N}(0, R_k(\chi_k, s_k)) \\
\text{action:} \quad & u_k = (a_k, \phi_k) \\
\text{state transition:} \quad & x_{k+1} = T(x_k, u_k, v_k, w_{k+1}), \quad v_k \sim \mathcal{N}(0, Q_k) \\
\text{belief state:} \quad & b_k = (b_k^s, b_k^{\chi}, b_k^{\xi}, b_k^P)
\end{aligned}
$$

$$
\begin{aligned}
b_k^s(s) &= \delta(s - s_k) \\
b_k^{\chi} & \quad \text{updated with } z_k \text{ using Bayes theorem} \\
b_k^{\xi}(\xi) &= \delta(\xi - \xi_k) \\
b_k^P(P) &= \delta(P - P_k)
\end{aligned}
$$

POMDP Formulation

$$
\begin{aligned}
\text{state:} \quad & x_k = (s_k, \chi_k, \xi_k, P_k) \\
\text{measurement:} \quad & z_k^{\chi} = h(\chi_k, s_k) + w_k, \quad w_k \sim \mathcal{N}(0, R_k(\chi_k, s_k)) \\
\text{action:} \quad & u_k = (a_k, \phi_k) \\
\text{state transition:} \quad & x_{k+1} = T(x_k, u_k, v_k, w_{k+1}), \quad v_k \sim \mathcal{N}(0, Q_k) \\
\text{belief state:} \quad & b_k = (b_k^s, b_k^{\chi}, b_k^{\xi}, b_k^P) \\
\text{cost:} \quad & C(x_k, u_k) = \mathrm{E}_{v_k, w_{k+1}} \left[\left\| \chi_{k+1} - \xi_{k+1} \right\|^2 \middle| x_k, u_k \right]
\end{aligned}
$$

POMDP Solution

- Objective is to minimize

$$J_H = \mathrm{E}\left[\sum_{k=0}^{H-1} C(x_k, u_k)\right]$$

- Objective can be posed over belief states

$$J_H = \mathrm{E}\left[\sum_{k=0}^{H-1} c(b_k, u_k) \middle| b_0\right]$$

- Solution is a belief state feedback policy: $u_k = \pi_k(b_k)$
  Bellman's principle:

$$\begin{aligned} J_H^*(b_0) &= \min_a \left\{c(b_0, a) + \mathrm{E}\left[J_{H-1}^*(b_1) \middle| b_0, a\right]\right\} \\ &= \min_a Q_H(b_0, a) \qquad (\text{“}Q\text{-value”}) \\ \pi_0^*(b_0) &= \operatorname*{argmin}_a Q_H(b_0, a) \end{aligned}$$

- Hard to compute Q-value exactly!

POMDP Solution

- Objective is to minimize

$$J_H = \mathrm{E}\left[\sum_{k=0}^{H-1} C(x_k, u_k)\right]$$

- Objective can be posed over belief states

$$J_H = \mathrm{E}\left[\sum_{k=0}^{H-1} c(b_k, u_k) \middle| b_0\right]$$

- Solution is a belief state feedback policy: $u_k = \pi_k(b_k)$
  Bellman's principle:

$$\begin{aligned} J_H^*(b_0) &= \min_a \left\{c(b_0, a) + \mathrm{E}\left[J_{H-1}^*(b_1) \middle| b_0, a\right]\right\} \\ &= \min_a Q_H(b_0, a) \qquad (\text{“}Q\text{-value”}) \\ \pi_0^*(b_0) &= \operatorname*{argmin}_a Q_H(b_0, a) \end{aligned}$$

- Hard to compute Q-value exactly!

POMDP Solution

- Objective is to minimize

$$J_H = \mathrm{E}\left[\sum_{k=0}^{H-1} C(x_k, u_k)\right]$$

- Objective can be posed over belief states

$$J_H = \mathrm{E}\left[\sum_{k=0}^{H-1} c(b_k, u_k)\middle| b_0\right]$$

- Solution is a belief state feedback policy: $u_k = \pi_k(b_k)$
  Bellman's principle:

$$\begin{aligned} J_H^*(b_0) &= \min_a \left\{c(b_0, a) + \mathrm{E}\left[J_{H-1}^*(b_1)\middle| b_0, a\right]\right\} \\ &= \min_a Q_H(b_0, a) \qquad (\text{“}Q\text{-value”}) \\ \pi_0^*(b_0) &= \operatorname*{argmin}_a Q_H(b_0, a) \end{aligned}$$

- Hard to compute Q-value exactly!

POMDP Solution

- Objective is to minimize

$$J_H = \mathrm{E}\left[\sum_{k=0}^{H-1} C(x_k, u_k)\right]$$

- Objective can be posed over belief states

$$J_H = \mathrm{E}\left[\sum_{k=0}^{H-1} c(b_k, u_k)\middle| b_0\right]$$

- Solution is a belief state feedback policy: $u_k = \pi_k(b_k)$
  Bellman's principle:

$$\begin{aligned} J_H^*(b_0) &= \min_a \left\{c(b_0, a) + \mathrm{E}\left[J_{H-1}^*(b_1)\middle| b_0, a\right]\right\} \\ &= \min_a Q_H(b_0, a) \qquad (\text{“}Q\text{-value”}) \\ \pi_0^*(b_0) &= \operatorname*{argmin}_a Q_H(b_0, a) \end{aligned}$$

- Hard to compute Q-value exactly!

Nominal Belief-State Optimization (NBO)

1. Define nominal belief state sequence $(\hat{b}_1, \ldots, \hat{b}_{H-1})$

$$b_{k+1} = \Phi(b_k, u_k, v_k, w_{k+1})$$

$$\Rightarrow \hat{b}_{k+1} = \Phi(\hat{b}_k, u_k, 0, 0)$$
$$\hat{b}_0 = b_0$$

Nominal Belief-State Optimization (NBO)

1. Define nominal belief state sequence $(\hat{b}_1, \ldots, \hat{b}_{H-1})$
2. Replace expectation over random future belief states

$$J_H(b_0) = \underset{b_1,\ldots,b_H}{\mathrm{E}}\left[\sum_k c(b_k, u_k)\middle| b_0\right]$$

with the sample given by nominal belief state sequence

$$J_H(b_0) \approx \sum_k c(\hat{b}_k, u_k)$$

Nominal Belief-State Optimization (NBO)

1. Define nominal belief state sequence $(\hat{b}_1, \ldots, \hat{b}_{H-1})$
2. Replace expectation over random future belief states

$$J_H(b_0) = \underset{b_1,\ldots,b_H}{\mathrm{E}}\left[\sum_k c(b_k, u_k)\middle| b_0\right]$$

with the sample given by nominal belief state sequence

$$J_H(b_0) \approx \sum_k c(\hat{b}_k, u_k)$$

3. Objective function from NBO:

$$J_{\text{NBO}} = \sum_{k=0}^{H-1} \sum_{i=1}^{N_{\text{targets}}} \mathrm{Tr}\, \hat{P}^i_{k+1}$$

Nominal Belief-State Optimization (NBO)

1. Define nominal belief state sequence $(\hat{b}_1, \ldots, \hat{b}_{H-1})$
2. Replace expectation over random future belief states

$$J_H(b_0) = \underset{b_1,\ldots,b_H}{\mathrm{E}}\left[\sum_k c(b_k, u_k)\middle| b_0\right]$$

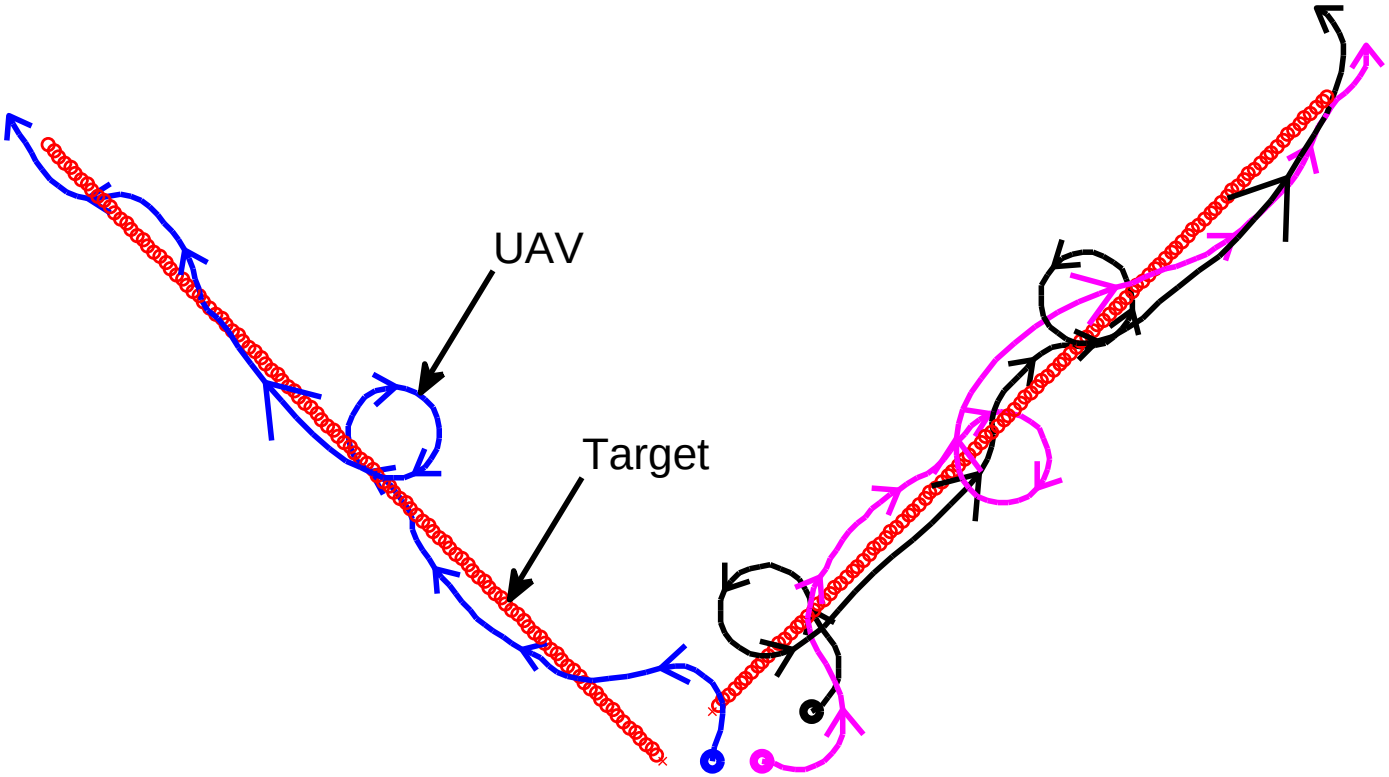
with the sample given by nominal belief state sequence

$$J_H(b_0) \approx \sum_k c(\hat{b}_k, u_k)$$

3. Objective function from NBO:

$$J_{\text{NBO}} = \sum_{k=0}^{H-1} \sum_{i=1}^{N_{\text{targets}}} \mathrm{Tr}\, \hat{P}^i_{k+1}$$

Three UAVs Tracking Two Targets



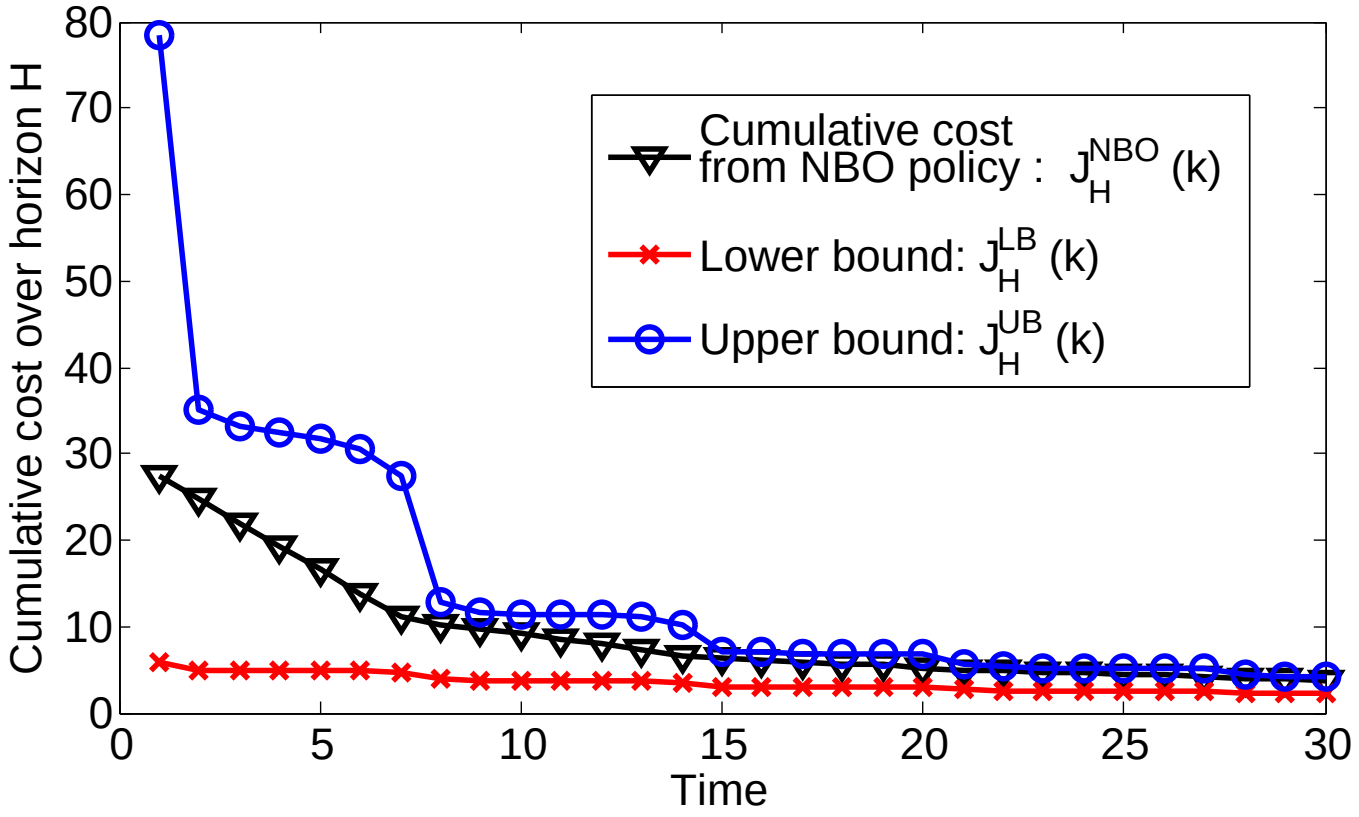
Stationary Target: Performance Bounds

Proposition

$$\sum_{i=1}^{N_{targs}} \sum_{k=0}^{H-1} \frac{M^2}{Tr\left[(\mathbf{P}_0^i)^{-1}\right] + (k+1)C} \leq J_H^*(b_0) \leq H \sum_{i=1}^{N_{targs}} Tr\mathbf{P}_0^i,$$

where M and C are constants

Performance comparison: 1 UAV and 1 Stationary Target



Enhancements

- Wind compensation
- Collision avoidance
- Track swap avoidance
- Tracking evasive targets
- Threat evasion

Decentralized UAV Guidance for Tracking Multiple Targets

Publications

S. Ragi and E. K. P. Chong, "Decentralized control of unmanned aerial vehicles for multitarget tracking," *Proc. 2013 Int. Conf. Unmanned Aircraft Systems*, submitted for publication.

Problem Specification

Targets

Problem Specification

Targets

Unmanned aerial vehicles (also called agents)

- the locations and velocities of every UAV in the system are available at each UAV

Problem Specification

Targets

Unmanned aerial vehicles (also called agents)

Spatially varying measurement errors

Problem Specification

Targets

Unmanned aerial vehicles (also called agents)

Spatially varying measurement errors

Communication

- each UAV can transmit and receive information to/from other UAVs

Problem Specification

Targets

Unmanned aerial vehicles (also called agents)

Spatially varying measurement errors

Communication

Tracker

Problem Specification

Targets

Unmanned aerial vehicles (also called agents)

Spatially varying measurement errors

Communication

Tracker

Objective

- optimize UAV controls, in a decentralized setting, such that a composite cost metric, a weighted sum of the mean-squared error and the cost of communication, is minimized

Communication Between the Agents

- Agents communicate over an underlying network
- *Communication link*—the end-to-end path through the network between a pair of agents
- *Link usage cost*—proportional to the distance between the two associated agents
- Further assumptions
  - an agent can communicate with at most one other agent at any decision epoch
  - an agent can send one of the L locally generated target observations in the past L time-steps to a chosen destination (agent)

Key Components of Dec-POMDP

agents: set of agents $\mathcal{I} = \{1, \ldots, N\}$

Key Components of Dec-POMDP

agents: set of agents $\mathcal{I} = \{1, \ldots, N\}$

state: $x_k = (s_k, \chi_k, T_k)$

- UAV state s_k
- target state χ_k
- track state $T_k = (T_k^1, \ldots, T_k^N)$, where $T_k^i = (\xi_k^i, P_k^i)$ is the state of the tracking algorithm at agent i

Key Components of Dec-POMDP

agents: set of agents $\mathcal{I} = \{1, \ldots, N\}$

state: $x_k = (s_k, \chi_k, T_k)$

measurement: $z_k = (z_k^1, \ldots, z_k^N)$, where z_k^i is the local observation at agent i

Key Components of Dec-POMDP

agents: set of agents $\mathcal{I} = \{1, \ldots, N\}$

state: $x_k = (s_k, \chi_k, T_k)$

measurement: $z_k = (z_k^1, \ldots, z_k^N)$, where z_k^i is the local observation at agent i

action: $u_k = (u_k^1, \ldots, u_k^N)$, where u_k^i is the action-vector at agent i
$u_k^i = (a_k^i, g_k^i, l_k^i)$, where a_k^i is the kinematic control command, g_k^i is the ID of agent $(\neq i)$ to whom i will send its locally generated target observation at time $l_k^i \in \{k, \ldots, k - L\}$ in the past

Key Components of Dec-POMDP

agents: set of agents $\mathcal{I} = \{1, \ldots, N\}$

state: $x_k = (s_k, \chi_k, T_k)$

measurement: $z_k = (z_k^1, \ldots, z_k^N)$, where z_k^i is the local observation at agent i

action: $u_k = (u_k^1, \ldots, u_k^N)$, where u_k^i is the action-vector at agent i

state transition: $x_{k+1} \sim p_k(\cdot | x_k, u_k)$

$$s_{k+1} = \psi(s_k, u_k)$$
$$\chi_{k+1} = F\chi_k + e_k$$

The track states at each agent i are updated according to the Kalman filter equations given the local observations and the information received from other agents

Key Components of Dec-POMDP

agents: set of agents $\mathcal{I} = \{1, \ldots, N\}$

state: $x_k = (s_k, \chi_k, T_k)$

measurement: $z_k = (z_k^1, \ldots, z_k^N)$, where z_k^i is the local observation at agent i

action: $u_k = (u_k^1, \ldots, u_k^N)$, where u_k^i is the action-vector at agent i

state transition: $x_{k+1} \sim p_k(\cdot | x_k, u_k)$

cost: $C(x_k, u_k) =$ weighted mean of the mean-squared tracking error and the cost of communication

Objective and Optimal Policy

- Minimize

$$J_H = \mathrm{E}\left[\sum_{k=0}^{H-1} C(x_k, u_k)\right]$$

- The optimal policy for the centralized system is

$$\pi^*(b_0) = \arg\min_u Q(b_0, u),$$

where

$$Q(b_0, u) = c(b_0, u) + \mathrm{E}[J_H^*(b_1) \,|\, b_0, u]\,,$$

- For the decentralized case, our approach is

$$\pi^i(b_k^i) = \arg\min_u Q(b_k^i, u), \quad i = 1, \ldots, N$$

where b_k^i is the local belief-state at i

- The objective function from NBO at agent i is

$$J_{\mathrm{NBO}}(b_0^i) = \sum_{k=0}^{H-1} \left(\mathrm{Tr}\,\hat{\mathbf{P}}_{k+1}^i + \beta \hat{d}_k^{i,g_k^i}\right)$$

Objective and Optimal Policy

- Minimize

$$J_H = \mathrm{E}\left[\sum_{k=0}^{H-1} C(x_k, u_k)\right]$$

- The optimal policy for the centralized system is

$$\pi^*(b_0) = \arg\min_u Q(b_0, u),$$

where

$$Q(b_0, u) = c(b_0, u) + \mathrm{E}[J_H^*(b_1) \,|\, b_0, u]\,,$$

- For the decentralized case, our approach is

$$\pi^i(b_k^i) = \arg\min_u Q(b_k^i, u), \quad i = 1, \ldots, N$$

where b_k^i is the local belief-state at i

- The objective function from NBO at agent i is

$$J_{\mathrm{NBO}}(b_0^i) = \sum_{k=0}^{H-1} \left(\mathrm{Tr}\,\hat{\mathbf{P}}_{k+1}^i + \beta \hat{d}_k^{i,g_k^i}\right)$$

Objective and Optimal Policy

- Minimize

$$J_H = \mathrm{E}\left[\sum_{k=0}^{H-1} C(x_k, u_k)\right]$$

- The optimal policy for the centralized system is

$$\pi^*(b_0) = \arg\min_u Q(b_0, u),$$

where

$$Q(b_0, u) = c(b_0, u) + \mathrm{E}[J_H^*(b_1) \,|\, b_0, u]\,,$$

- For the decentralized case, our approach is

$$\pi^i(b_k^i) = \arg\min_u Q(b_k^i, u), \quad i = 1, \ldots, N$$

where b_k^i is the local belief-state at i

- The objective function from NBO at agent i is

$$J_{\mathrm{NBO}}(b_0^i) = \sum_{k=0}^{H-1} \left(\mathrm{Tr}\,\hat{\mathbf{P}}_{k+1}^i + \beta \hat{d}_k^{i,g_k^i}\right)$$

Objective and Optimal Policy

- Minimize

$$J_H = \mathrm{E}\left[\sum_{k=0}^{H-1} C(x_k, u_k)\right]$$

- The optimal policy for the centralized system is

$$\pi^*(b_0) = \arg\min_u Q(b_0, u),$$

where

$$Q(b_0, u) = c(b_0, u) + \mathrm{E}[J_H^*(b_1) \,|\, b_0, u]\,,$$

- For the decentralized case, our approach is

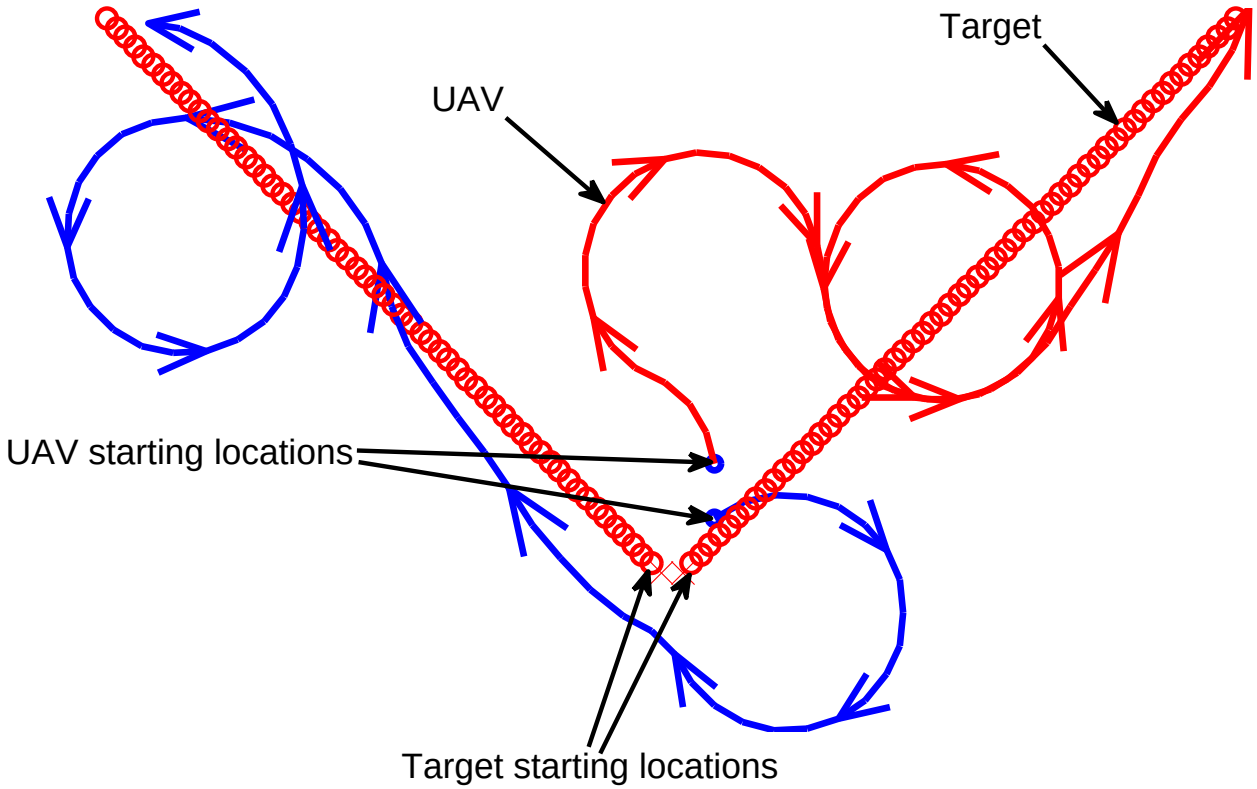
$$\pi^i(b_k^i) = \arg\min_u Q(b_k^i, u), \quad i = 1, \ldots, N$$

where b_k^i is the local belief-state at i

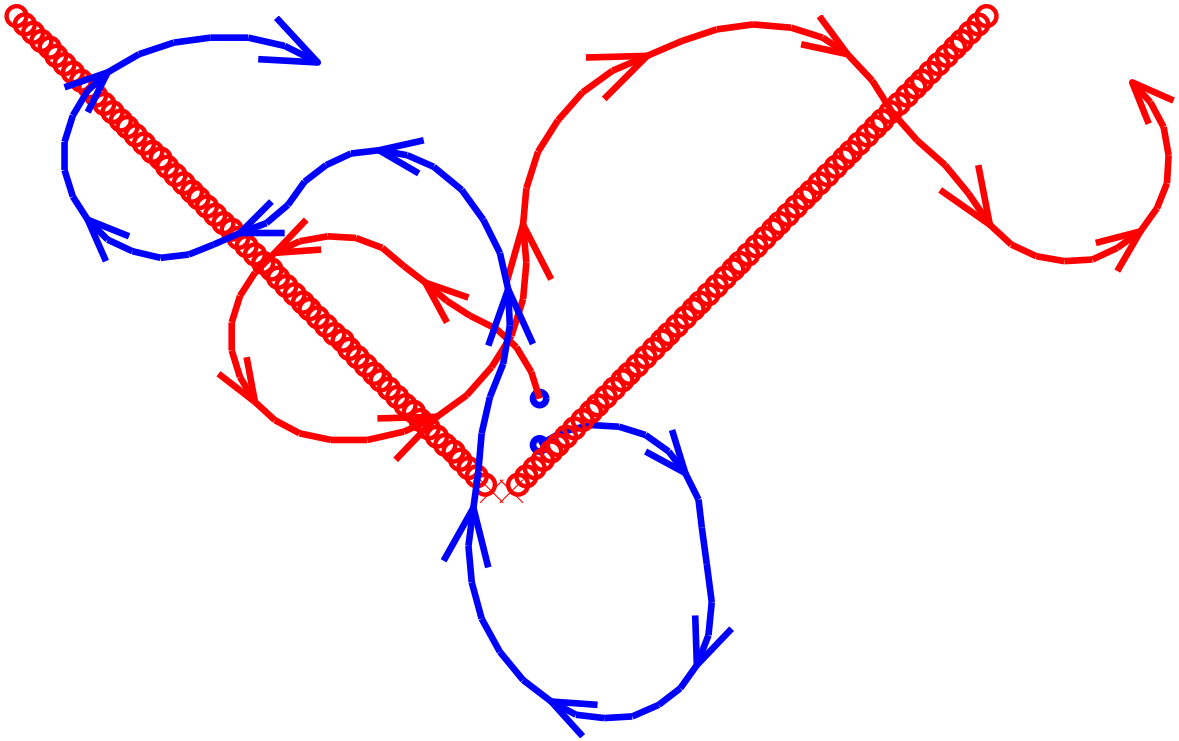
- The objective function from NBO at agent i is

$$J_{\mathsf{NBO}}(b_0^i) = \sum_{k=0}^{H-1} \left(\mathsf{Tr}\,\hat{\mathbf{P}}_{k+1}^i + \beta \hat{d}_k^{i,g_k^i}\right)$$

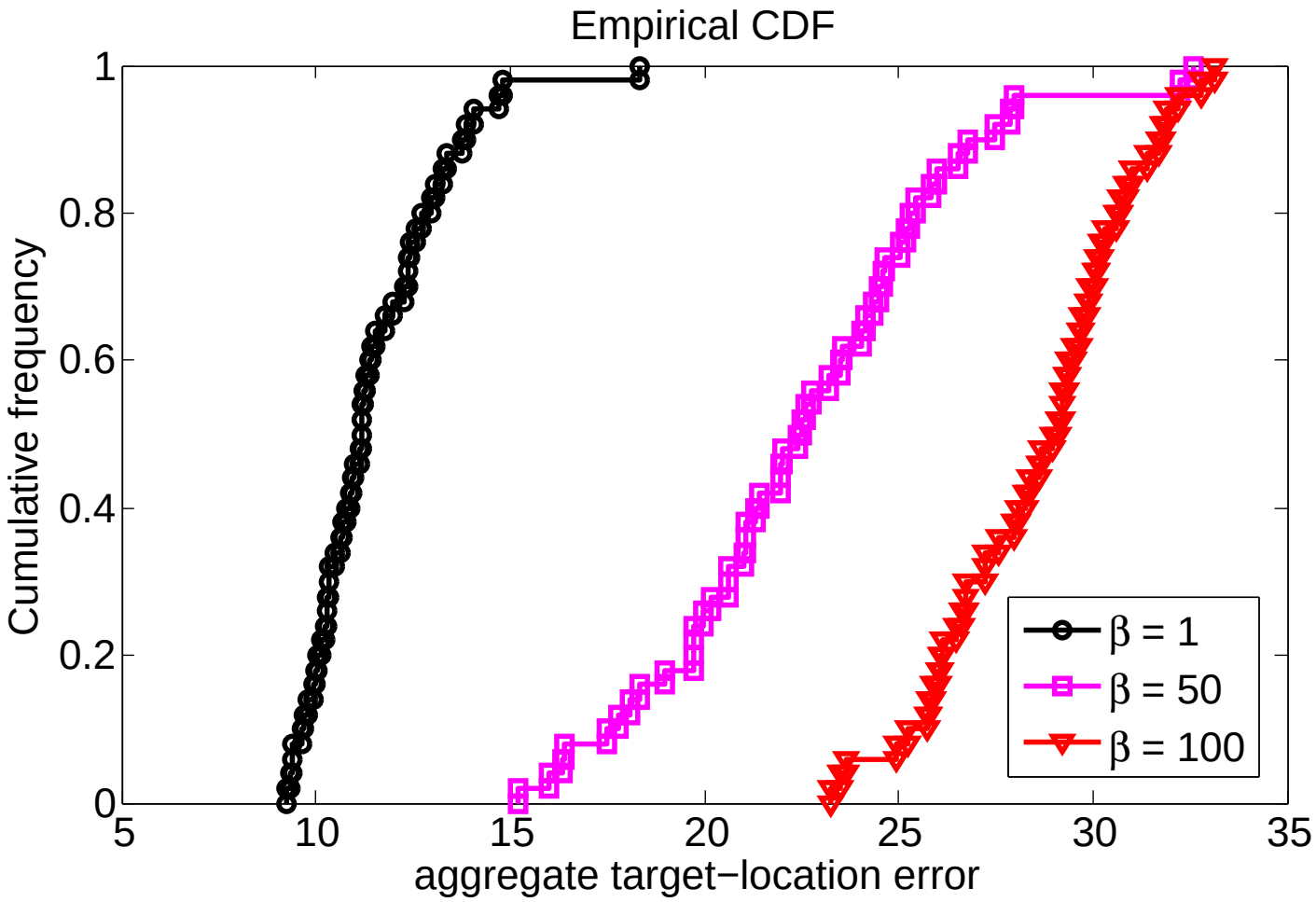
Two UAVs Tracking Two Targets; $\beta = 1$



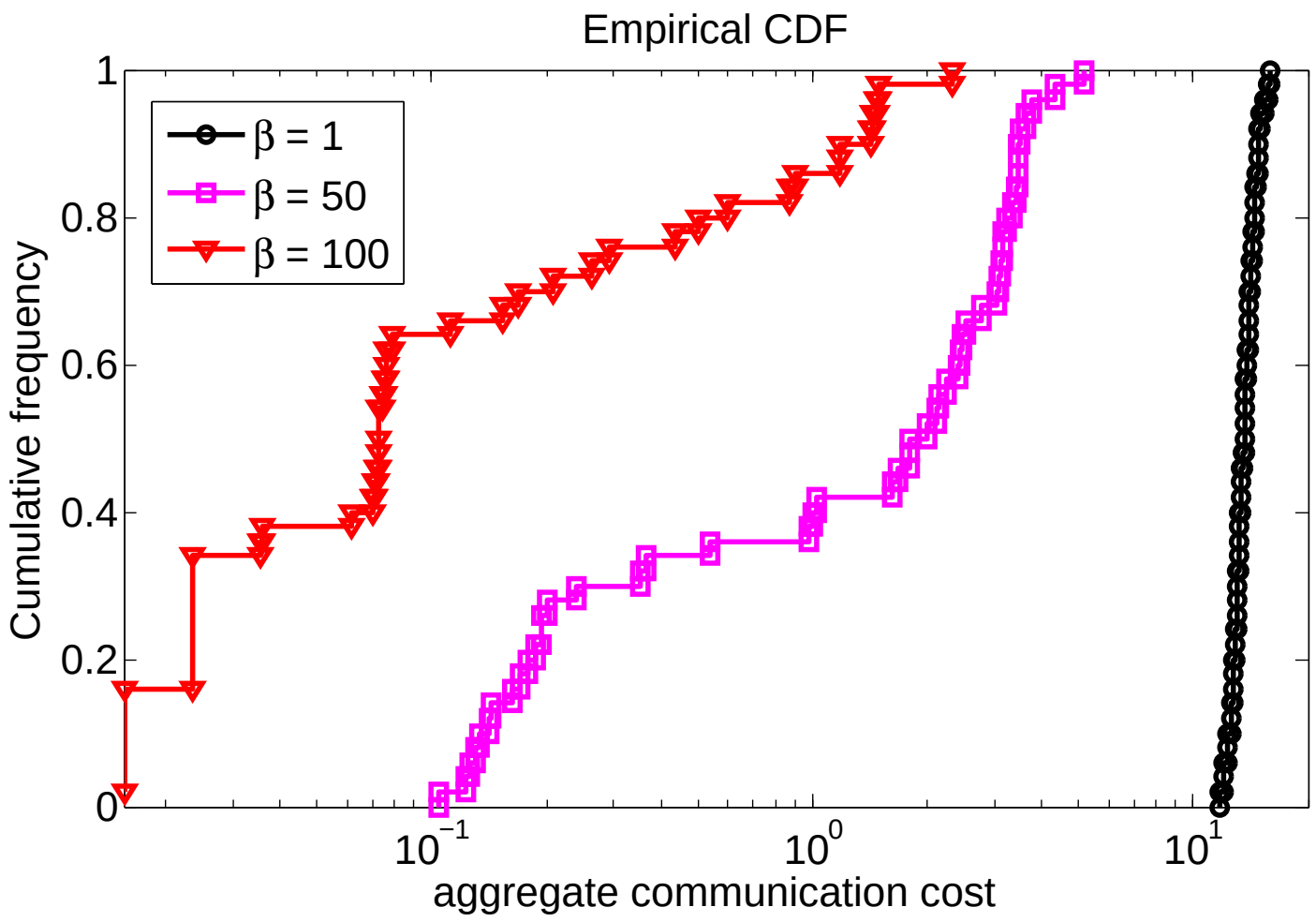
Two UAVs Tracking Two Targets; $\beta = 100$



Average Target Location Error



Average Communication Cost

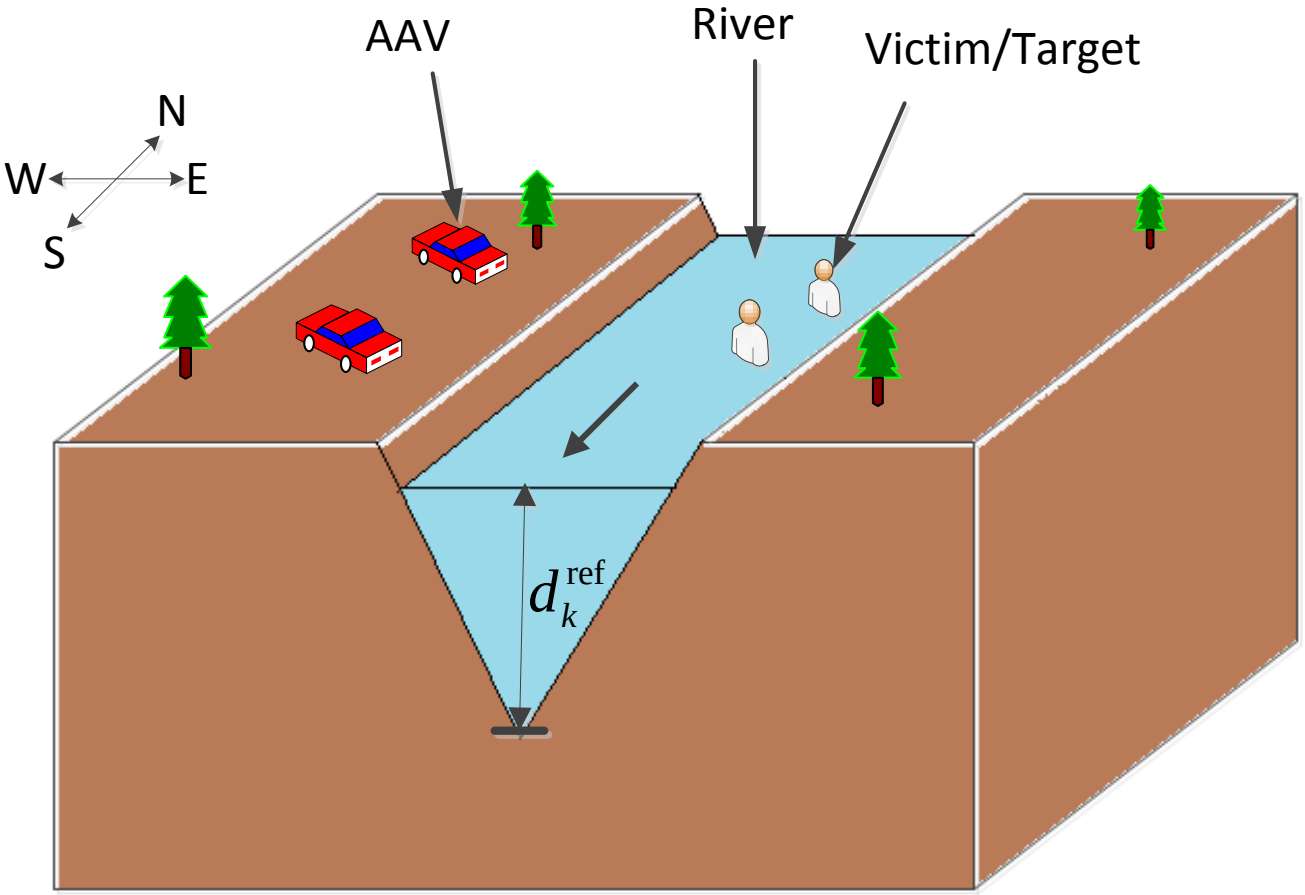


Autonomous Amphibious Vehicle (AAV) Guidance for Flood Rescue Support

Publications

1. S. Ragi, C. S. Tan, and E. K. P. Chong, "Guidance of autonomous amphibious vehicles for flood rescue support," *Math. Probl. Eng.*, special issue on *Math. Model. Resources and Environmental Syst.*, submitted for publication.
2. S. Ragi, C. S. Tan, and E. K. P. Chong, "Feasibility study of POMDP in autonomous amphibious vehicle guidance," in *2013 IFAC Symp. Intelligent Autonomous Vehicles*, to be published.

Flood Scenario



POMDP Formulation

state: $x_k = (s_k, d_k^{\text{ref}}, \chi_k, \xi_k^{\text{riv}}, P_k^{\text{riv}}, \xi_k^{\text{targ}}, P_k^{\text{targ}})$

- AAV state s_k
- river state d_k^{ref}
- target state χ_k
- track states $(\xi_k^{\text{riv}}, P_k^{\text{riv}}, \xi_k^{\text{targ}}, P_k^{\text{targ}})$

POMDP Formulation

state: $x_k = (s_k, d_k^{\text{ref}}, \chi_k, \xi_k^{\text{riv}}, P_k^{\text{riv}}, \xi_k^{\text{targ}}, P_k^{\text{targ}})$

measurement: sensor and the track states are fully observable; noisy observations of river and target states are available

POMDP Formulation

state: $x_k = (s_k, d_k^{\text{ref}}, \chi_k, \xi_k^{\text{riv}}, P_k^{\text{riv}}, \xi_k^{\text{targ}}, P_k^{\text{targ}})$

measurement: sensor and the track states are fully observable; noisy observations of river and target states are available

action: $u_k = (g_k, a_k)$

- g_k represents a one-to-one correspondence between AAVs and targets
- a_k includes forward accelerations and steering angles for each AAV

POMDP Formulation

state: $x_k = (s_k, d_k^{\text{ref}}, \chi_k, \xi_k^{\text{riv}}, P_k^{\text{riv}}, \xi_k^{\text{targ}}, P_k^{\text{targ}})$

measurement: sensor and the track states are fully observable; noisy observations of river and target states are available

action: $u_k = (g_k, a_k)$

state transition: $x_{k+1} = T(x_k, u_k, e_k^{\text{targ}}, e_k^{\text{riv}}, n_{k+1}^{\text{targ}}, n_{k+1}^{\text{riv}})$,

$e_k^{\text{targ}} \sim \mathcal{N}(0, Q_k^{\text{targ}}), e_k^{\text{targ}} \sim \mathcal{N}(0, Q_k^{\text{targ}})$

$$\chi_{k+1} = F\chi_k + e_k^{\text{targ}}$$
$$d_{k+1}^{\text{ref}} = d_k^{\text{ref}} + e_k^{\text{riv}}$$

AAV state evolves according to the AAV kinematic motion model. Track states are updated according to Kalman filter equations

POMDP Formulation

state: $x_k = (s_k, d_k^{\text{ref}}, \chi_k, \xi_k^{\text{riv}}, P_k^{\text{riv}}, \xi_k^{\text{targ}}, P_k^{\text{targ}})$

measurement: sensor and the track states are fully observable; noisy observations of river and target states are available

action: $u_k = (g_k, a_k)$

state transition: $x_{k+1} = T(x_k, u_k, e_k^{\text{targ}}, e_k^{\text{riv}}, n_{k+1}^{\text{targ}}, n_{k+1}^{\text{riv}})$,

$e_k^{\text{targ}} \sim \mathcal{N}(0, Q_k^{\text{targ}}), e_k^{\text{targ}} \sim \mathcal{N}(0, Q_k^{\text{targ}})$

cost: $C(x_k, u_k) =$

$$\sum_{i=1}^{N} \mathbf{1}\left\{ \mathsf{E}\left[\left\| s_{k+1}^{i,\text{pos}} - \xi_{k+1}^{g_k(i),\text{targ,pos}} \right\| \,\middle|\, x_k, u_k \right] > d_{\text{dist-thresh}} \right\},$$

Objective Function and Solution

- The objective function in terms of the belief states is

$$J_H(b_0) = \mathrm{E}\left[\sum_{k=0}^{H-1} c(b_k, u_k) \,\middle|\, b_0\right],$$

- NBO approach with distance-based ECTG

$$J_{\text{NBO}}(b_0) = \sum_{k=0}^{H-1}\sum_{i=1}^{N} \mathbf{1}\left\{\left\|\hat{s}_{k+1}^{i,\text{pos}} - \hat{\xi}_{k+1}^{g(i),\text{targ,pos}}\right\| > d_{\text{dist-thresh}}\right\} + J_H^{\text{dist-ECTG}},$$

where

$$J_H^{\text{dist-ECTG}} = \sum_{i=1}^{N} \left\|\hat{s}_H^{i,\text{pos}} - \hat{\xi}_H^{g(i),\text{targ,pos}}\right\|,$$

Objective Function and Solution

- The objective function in terms of the belief states is

$$J_H(b_0) = \mathrm{E}\left[\sum_{k=0}^{H-1} c(b_k, u_k) \,\middle|\, b_0\right],$$

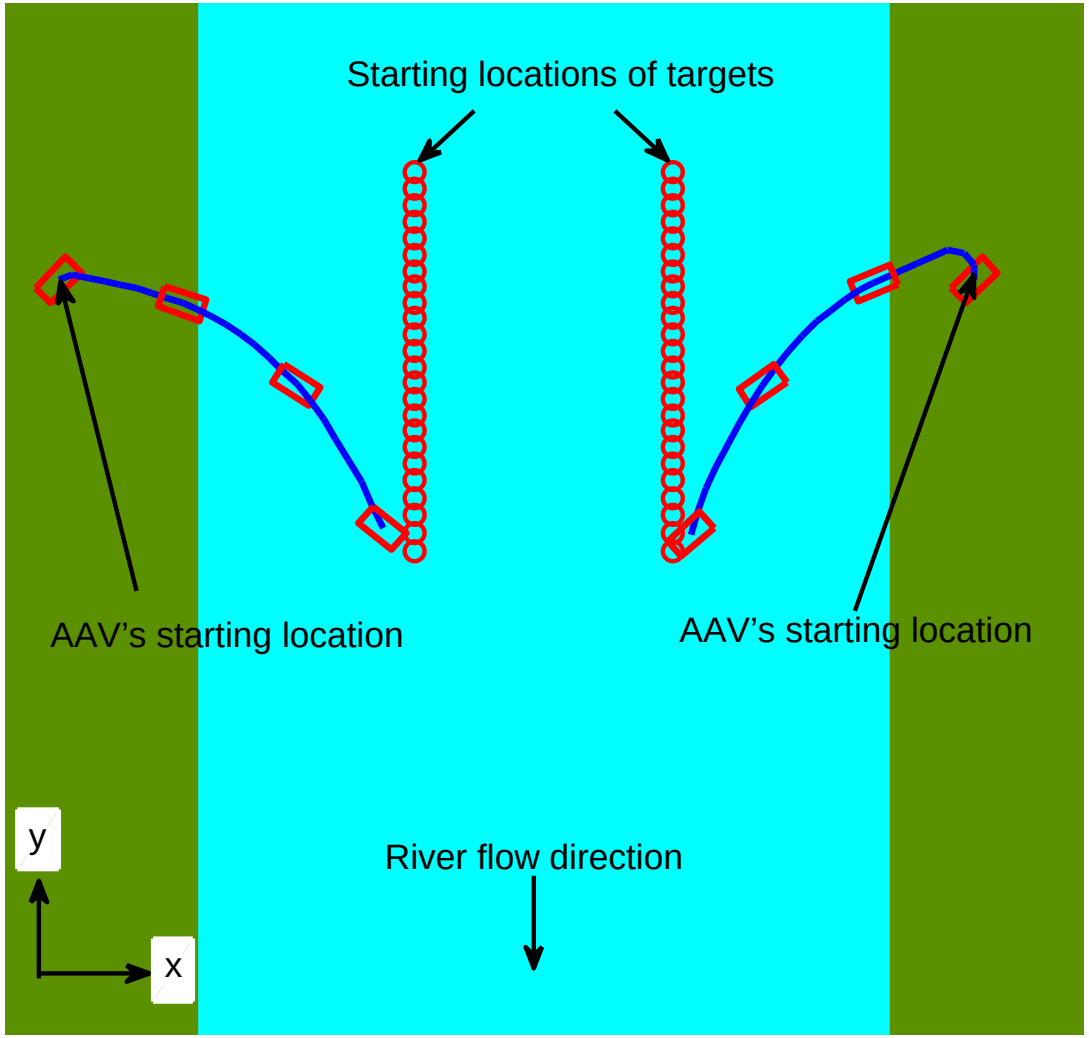
- NBO approach with distance-based ECTG

$$J_{\text{NBO}}(b_0) = \sum_{k=0}^{H-1}\sum_{i=1}^{N} \mathbf{1}\left\{\left\|\hat{s}_{k+1}^{i,\text{pos}} - \hat{\xi}_{k+1}^{g(i),\text{targ,pos}}\right\| > d_{\text{dist-thresh}}\right\} + J_H^{\text{dist-ECTG}},$$

where

$$J_H^{\text{dist-ECTG}} = \sum_{i=1}^{N} \left\|\hat{s}_H^{i,\text{pos}} - \hat{\xi}_H^{g(i),\text{targ,pos}}\right\|,$$

2 AAVs and 2 Targets (or Flood Victims)



Proposed Work

Decentralized UAV Guidance (Extensions)

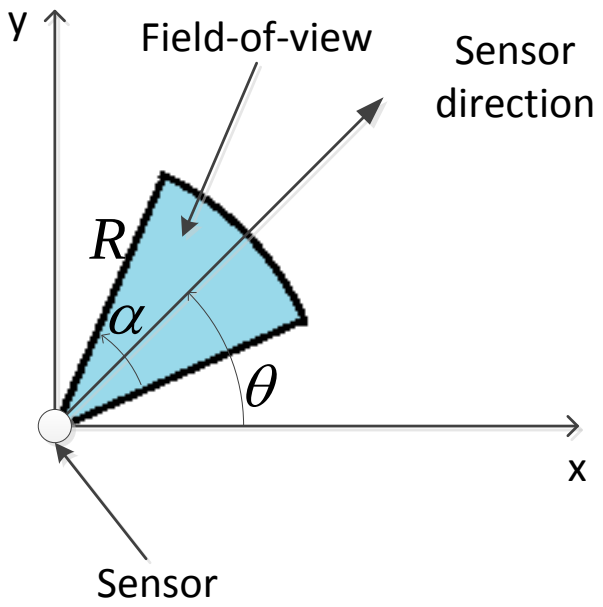
Extensions

- Dynamic (time-varying) network between the UAVs
- Explicit optimization of communication decisions among the UAVs at network level
- Incorporate communication delays

Directional Sensor Control

Directional Sensor

Limited field-of-view!



Problem Specification

Targets

- static or moving

Problem Specification

Targets

Directional Sensors

- set of possible directions for each sensor $\Theta = \{1, \ldots, K\}$
- control vector $u = (u_1, \ldots, u_M)$, $u_i \in \Theta$, $i = 1, \ldots, M$

Problem Specification

Targets

Directional Sensors

Measurement Errors

- measurement of a target is available only if the target lies within the field-of-view of a sensor
- spatially varying random (Gaussian) measurement errors

Problem Specification

Targets

Directional Sensors

Measurement Errors

Fusion Center

Problem Specification

Targets

Directional Sensors

Measurement Errors

Fusion Center

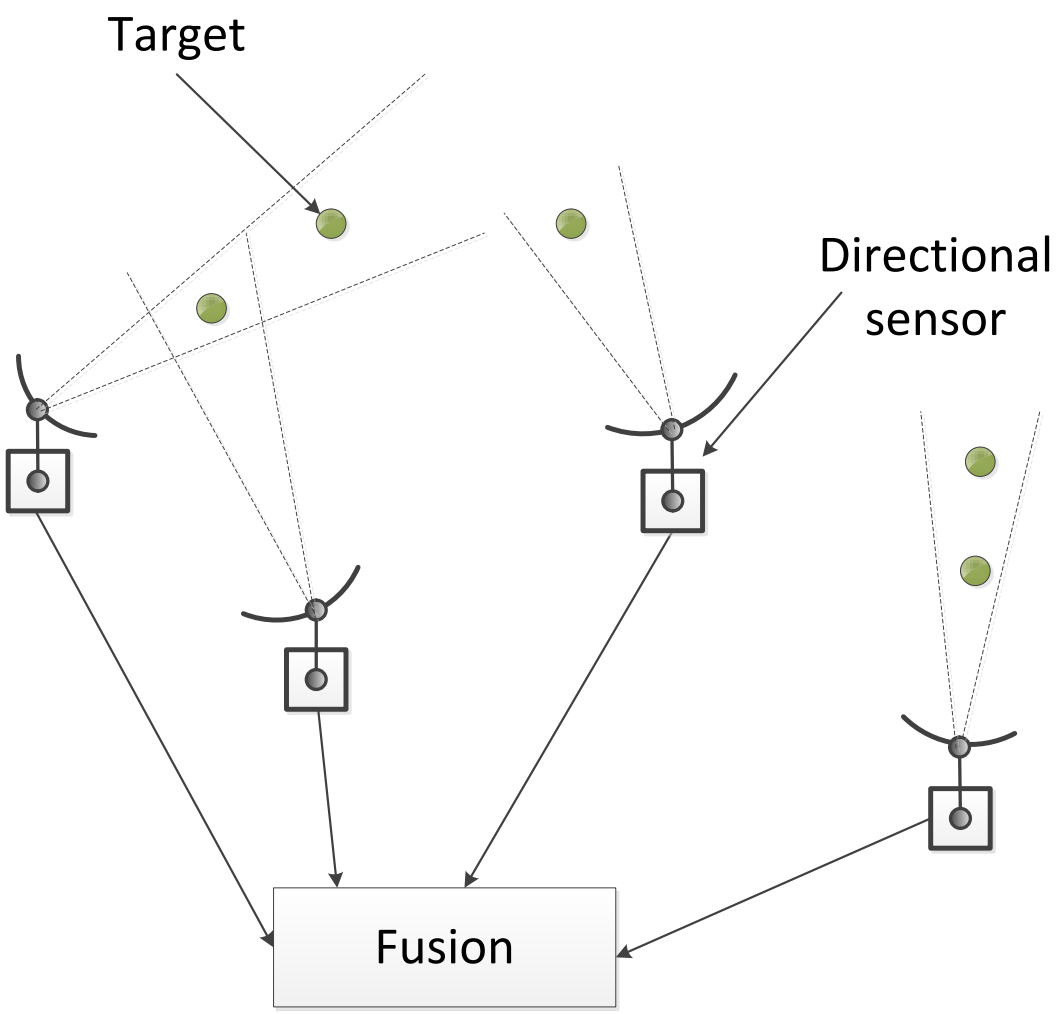
Objective

- find u such that the information gain is maximized

$$\mathrm{E}\left[\sum_{j=1}^{N} -\log\left(\det(\mathbf{P_j})\right)\right],$$

- a combinatorial optimization problem!

Example Scenario



Proposed Work

- Develop heuristic approaches for static targets
- Extend to dynamic target scenario—POMDP
- Extend to decentralized setting
  - Dec-POMDP formulation
  - optimize the communication decisions at network level (for a given network)
- Extend to video/camera network applications

Proposed Work

- Develop heuristic approaches for static targets
- Extend to dynamic target scenario—POMDP
- Extend to decentralized setting
  - Dec-POMDP formulation
  - optimize the communication decisions at network level (for a given network)
- Extend to video/camera network applications

Proposed Work

- Develop heuristic approaches for static targets
- Extend to dynamic target scenario—POMDP
- Extend to decentralized setting
  - Dec-POMDP formulation
  - optimize the communication decisions at network level (for a given network)
- Extend to video/camera network applications

Proposed Work

- Develop heuristic approaches for static targets
- Extend to dynamic target scenario—POMDP
- Extend to decentralized setting
  - Dec-POMDP formulation
  - optimize the communication decisions at network level (for a given network)
- Extend to video/camera network applications

Proposed Work

- Develop heuristic approaches for static targets
- Extend to dynamic target scenario—POMDP
- Extend to decentralized setting
  - Dec-POMDP formulation
  - optimize the communication decisions at network level (for a given network)
- Extend to video/camera network applications

Proposed Work

- Develop heuristic approaches for static targets
- Extend to dynamic target scenario—POMDP
- Extend to decentralized setting
  - Dec-POMDP formulation
  - optimize the communication decisions at network level (for a given network)
- Extend to video/camera network applications

Questions?