Institute for Systems and Robotics Lisboa

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EUMarineRobots webinar

Cooperative distributed estimation and control of multiple autonomous vehicles for range-based underwater target localization and pursuit

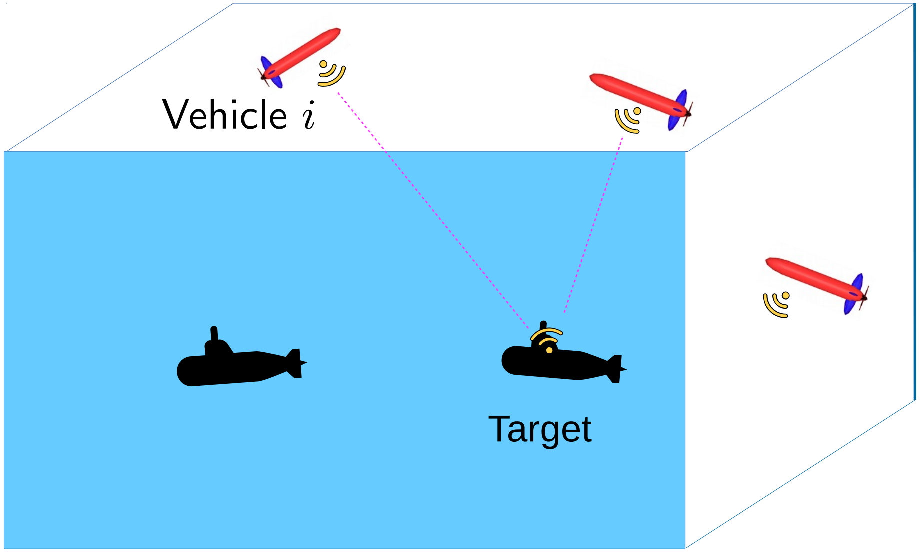
Speaker:

Nguyen Tuan Hung

Contact: nguyen.hung@tecnico.ulisboa.pt

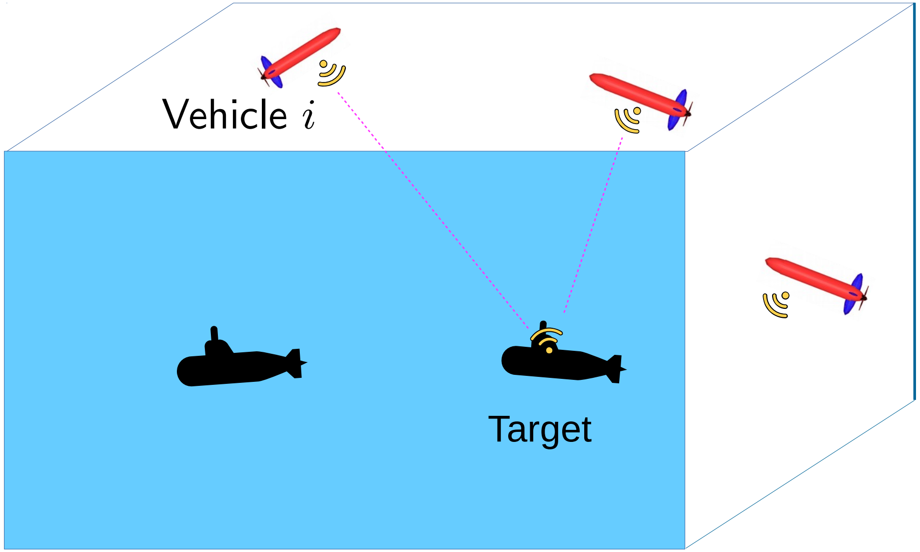
Joint work with:

Francisco Rego, Naveen Crasta, David Salinas, Antonio Pascoal, Tor Johansen



Problems

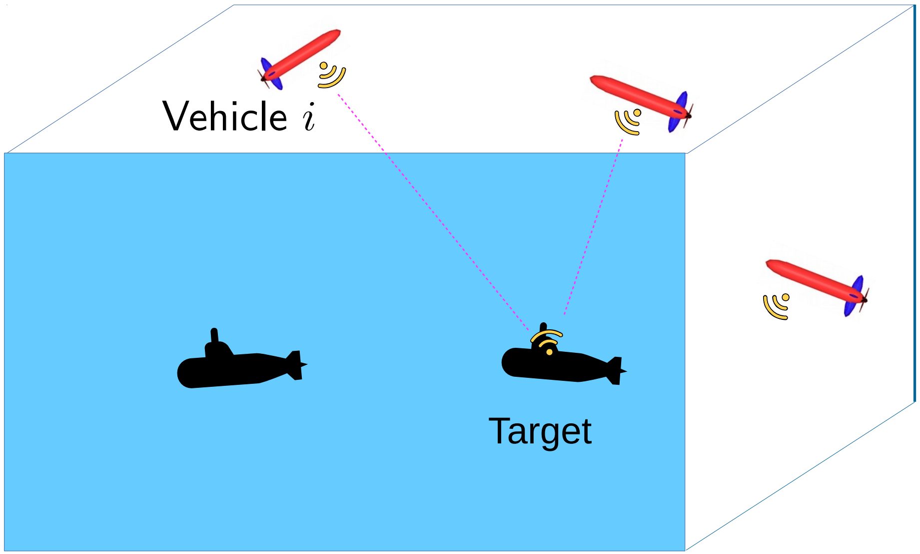
- How to localize the targets cooperatively ?
  - ensure that all vehicles have an agreement on the estimates of the targets' states
- How to pursue the targets cooperatively ?
  - keep the vehicles close to the targets
  - Keep the vehicles in a desired geometrical formation w.r.t. the targets



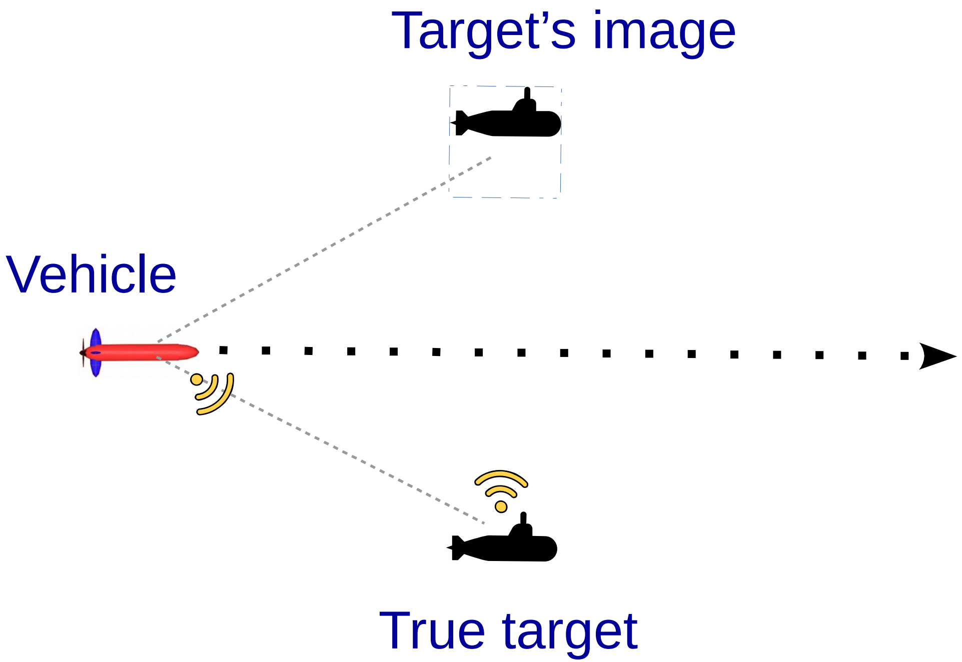
Solutions

- Centralized approach with tools from
  - Estimation theory (CRLB)
  - Model predictive control
- Distributed approach with tools from
  - Distributed estimation (distributed EKF)
  - Distributed control
  - Nonlinear control

Centralized approach with MPC and CRLB

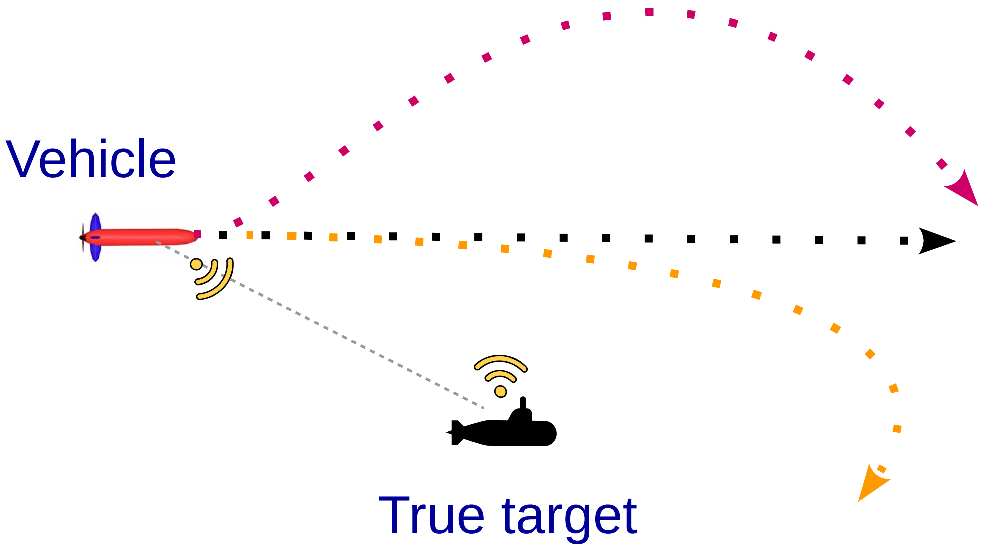


Target information ▷ measured by the Fisher Information Matrix (FIM)



Can not distinguish "True target" and Target's image
when using range measurements
(because the distances to the vehicle are equal)

Target information ▷ measured by the Fisher Information Matrix (FIM)



How to quantify the range-related information available to estimate the target´s state ?

↓

Fisher Information Matrix

Vehicles' model:

$$\mathbf{z}_{k+1}^{[i]} = \mathbf{g}_{\mathrm{d}}(\mathbf{z}_k^{[i]}, \mathbf{v}_k^{[i]}), i = 1, ..., p$$

$$\mathbf{p}_k^{[i]} = C\mathbf{z}_k^{[i]}$$

Input

Position

State

Prior information

Target model:

$$\mathbf{x}_{k+1} = \mathbf{f}(\mathbf{x}_k), \quad \mathbf{x}_0 \sim \mathcal{N}(\mathbf{c}_0, P_0)$$

$$\mathbf{q}_k = D\mathbf{x}_k$$

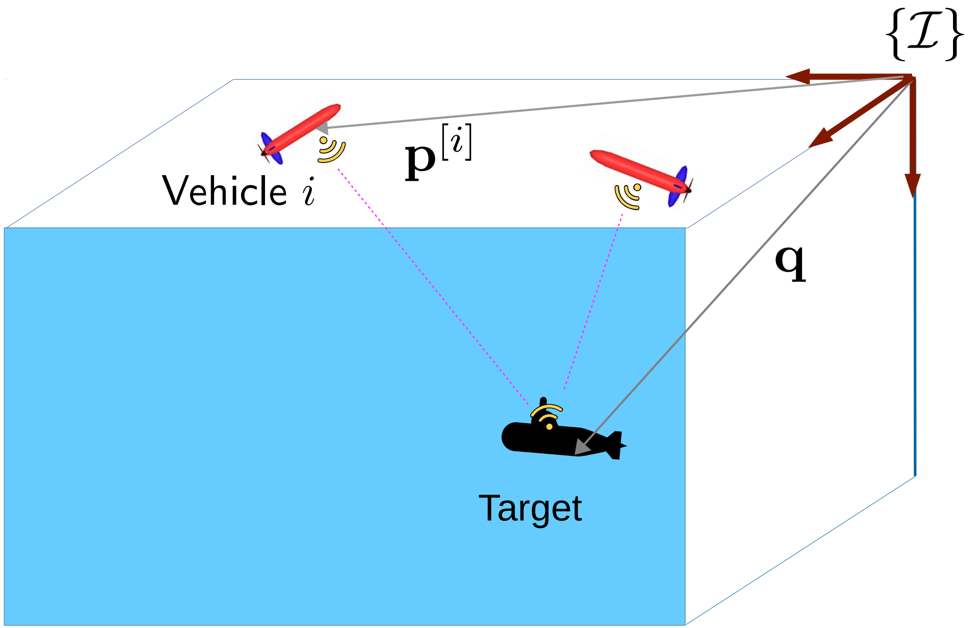
Position

State

noise

Range measurement model

$$y_k^{[i]} = \left\|\mathbf{p}_k^{[i]} - \mathbf{q}_k\right\| + \eta_k^{[i]}$$



Range-based SLAP using posterior CRLB ▷ Problem formulation

Vehicles' model:

$$\mathbf{z}_{k+1}^{[i]} = \mathbf{g}_{\mathrm{d}}(\mathbf{z}_k^{[i]}, \mathbf{v}_k^{[i]}), i = 1, ..., p$$

$$\mathbf{p}_k^{[i]} = C\mathbf{z}_k^{[i]}$$

Position ($\mathbf{p}_k^{[i]}$), State ($\mathbf{z}_k^{[i]}$), Input ($\mathbf{v}_k^{[i]}$)

Target model:

$$\mathbf{x}_{k+1} = \mathbf{f}(\mathbf{x}_k), \quad \mathbf{x}_0 \sim \mathcal{N}(\mathbf{c}_0, P_0)$$

Prior information ($\mathbf{x}_0 \sim \mathcal{N}(\mathbf{c}_0, P_0)$)

$$\mathbf{q}_k = D\mathbf{x}_k$$

Position ($\mathbf{q}_k$), State ($\mathbf{x}_k$)

Range measurement model

$$y_k^{[i]} = \left\| \mathbf{p}_k^{[i]} - \mathbf{q}_k \right\| + \eta_k^{[i]}$$

noise ($\eta_k^{[i]}$)

Problem 1 [Range-based SLAP]

Derive a control strategy for $\mathbf{v}^{[i]}$ s.t.

- The range-information acquired is "sufficiently rich" for target estimation purposes
- Ensure also that the vehicles converge to a predefined vinicity of the target

Range-based SLAP using posterior CRLB ▷ Main idea

Vehicles' model:

$$\mathbf{z}_{k+1}^{[i]} = \mathbf{g}_{\mathrm{d}}(\mathbf{z}_k^{[i]}, \mathbf{v}_k^{[i]}), i = 1, ..., p$$

$$\mathbf{p}_k^{[i]} = C\mathbf{z}_k^{[i]}$$

Input

Position

State

Prior information

Target model:

$$\mathbf{x}_{k+1} = \mathbf{f}(\mathbf{x}_k), \quad \mathbf{x}_0 \sim \mathcal{N}(\mathbf{c}_0, P_0)$$

$$\mathbf{q}_k = D\mathbf{x}_k$$

Position

State

noise

Range measurement model

$$y_k^{[i]} = \left\|\mathbf{p}_k^{[i]} - \mathbf{q}_k\right\| + \eta_k^{[i]}$$

Tychavsky et al., 1998

Fisher Information Matrix (FIM)

FIM depends on the vehicles' positions driven by the vehicles' inputs

$$\mathcal{I}_k\left(\mathbf{p}_0^{[i]}, \mathcal{N}(\mathbf{c}_0, P_0), \mathbf{v}_0^{[i]}, ..., \mathbf{v}_{k-1}^{[i]}\right)$$

Objective

Find $\mathbf{v}_k^{[i]}, k = 0, ..., i = 1, ..., p$

that maximizes the $\det$(FIM)

Range-based SLAP using posterior CRLB ▷ MPC scheme

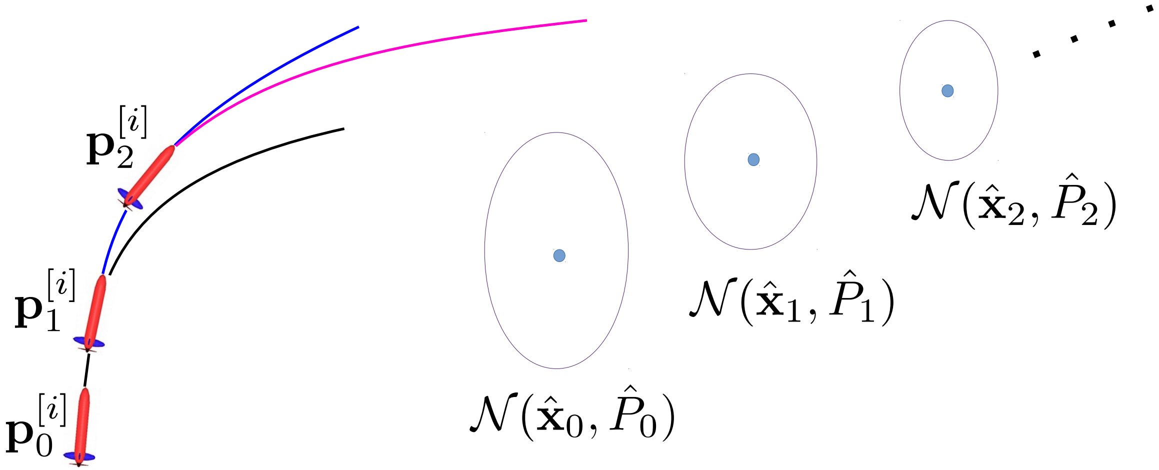
MPC strategy: at each sampling time k

i) $$(\bar{\mathbf{v}}_k^{[i]*}, ..., \bar{\mathbf{v}}_{k+N-1}^{[i]*}) = \underset{\substack{\bar{\mathbf{v}}_k^{[i]}, ..., \bar{\mathbf{v}}_{k+N-1}^{[i]} \\ i=1,...,p}}{\operatorname{argmax}} \underbrace{\det \bar{\mathcal{I}}\left(\mathbf{p}_k^{[i]}, \mathcal{N}(\hat{\mathbf{x}}_k, \hat{P}_k), \bar{\mathbf{v}}_k^{[i]}, ..., \bar{\mathbf{v}}_{k+N-1}^{[i]}\right)}_{\text{Predicted range-information over the prediction horizon } [k+1, k+N]}$$

ii) Control law for $\mathbf{v}^{[i]}$

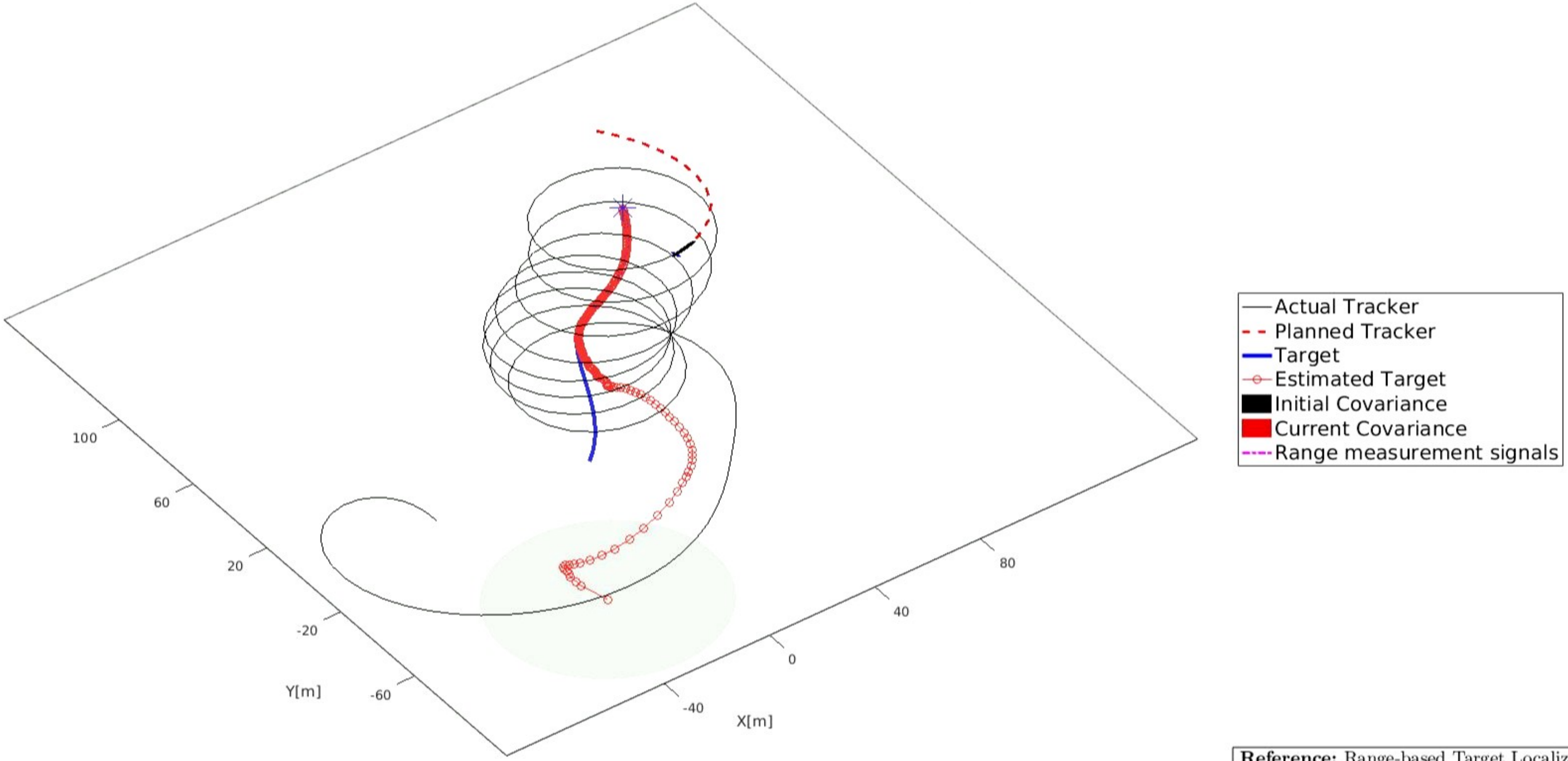
$$\mathbf{v}_k^{[i]} := \bar{\mathbf{v}}_k^{[i]*}, i = 1, ..., p$$

iii) Repeat



Range-based SLAP using posterior CRLB ▷ Example

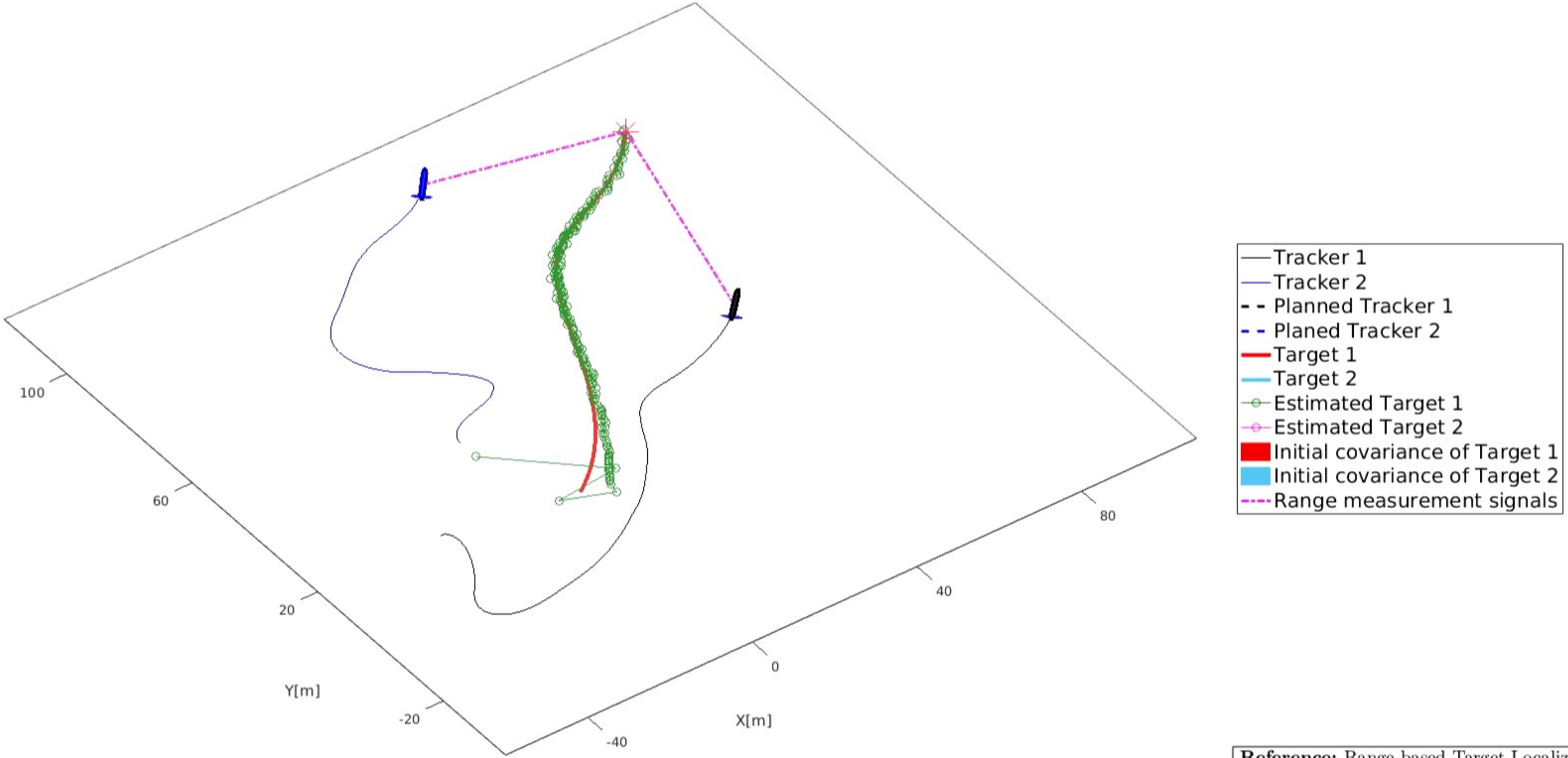
Range-based target localization and pursuit with autonomous vehicle (tracker) using MPC and Posterior CRLB



Reference: Range-based Target Localization and Pursuit with Autonomous Vehicles: An Approach using Posterior CRLB and Model Predictive Control, Nguyen T. Hung, Naveen Crasta, Antonio M. Pascoal, Tor A. Johansen, 2020

Range-based SLAP using posterior CRLB ▷ Example

Range-based target localization and pursuit with autonomous vehicles (trackers) using MPC and Posterior CRLB

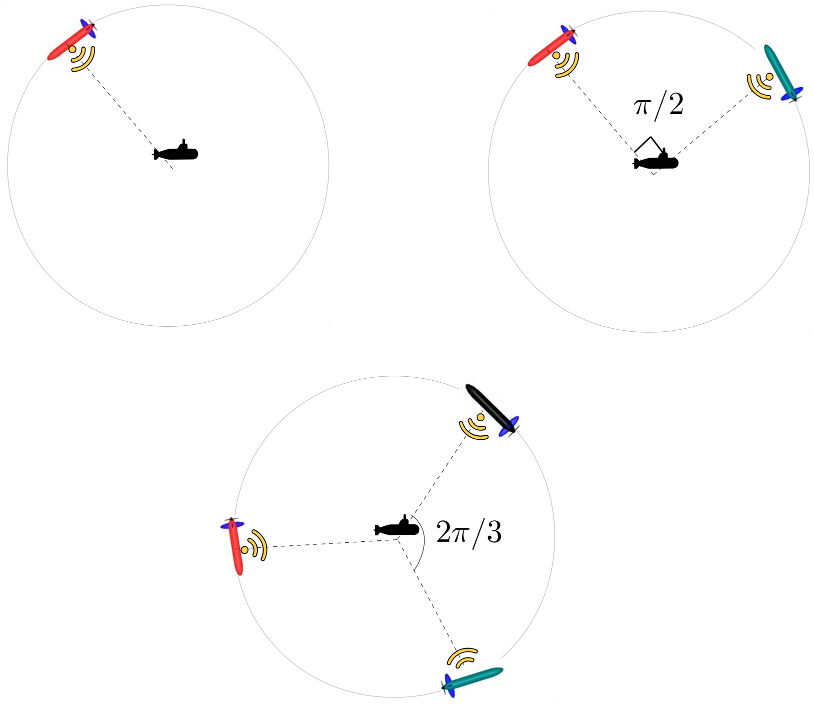


Reference: Range-based Target Localization and Pursuit with Autonomous Vehicles: An Approach using Posterior CRLB and Model Predictive Control, Nguyen T. Hung, Naveen Crasta, Antonio M. Pascoal, Tor A. Johansen, 2020

Summary

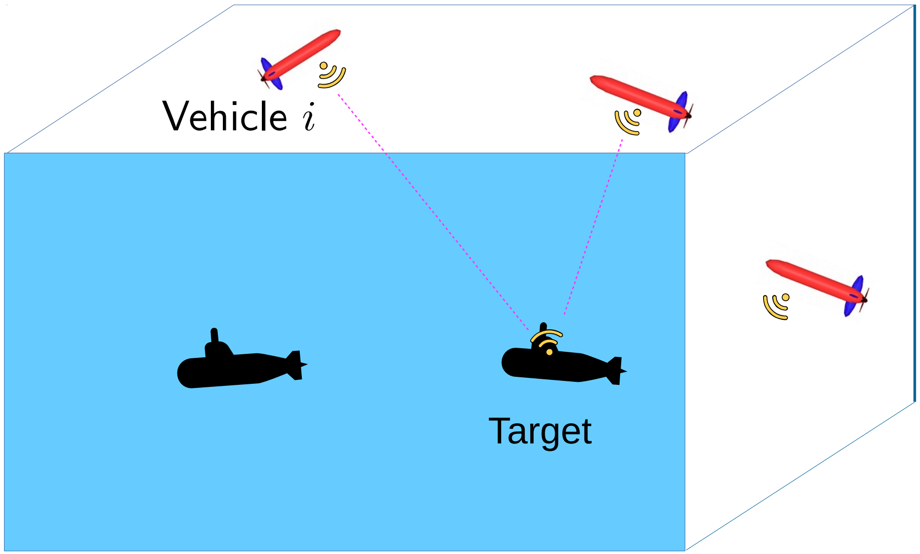
- MPC + CRLB is a universal approach
- Results give useful guidelines for motion planning
- However, for the case of multiple trackers, the MPC scheme is implemented in a centralized manner

See an alternative (distributed) approach next



Reference: Nguyen T. Hung, N. Crasta, David Moreno-Salinas, António M. Pascoal, Tor A. Johansen, “Range-based target localization and pursuit with autonomous vehicles: An approach using posterior CRLB and model predictive control”, Robotics and Autonomous Systems, 2020.

Distributed Approach



Vehicles' model (under-actuated vehicles)

$$\dot{\mathbf{p}}^{[i]} = R(\boldsymbol{\eta}^{[i]})\mathbf{v}^{[i]},$$

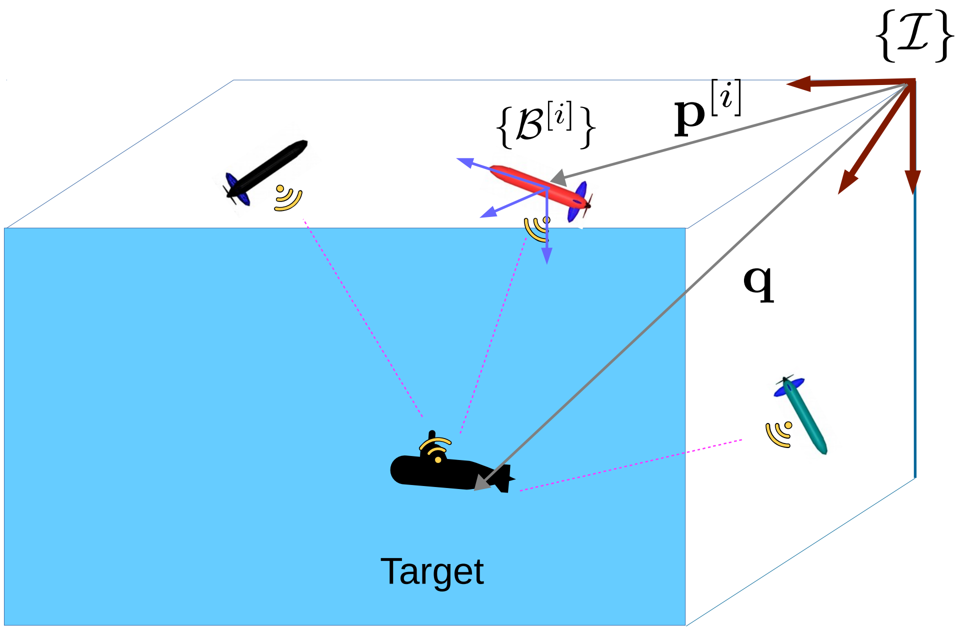
$$\dot{R}(\boldsymbol{\eta}^{[i]}) = R(\boldsymbol{\eta}^{[i]})S(\boldsymbol{\omega}^{[i]})$$

Skew matrix

Angular velocity

Rot. matrix from $\mathcal{B}^{[i]}$ to $\mathcal{I}$

$\mathbf{v}^{[i]}$: linear velocity



Target model:

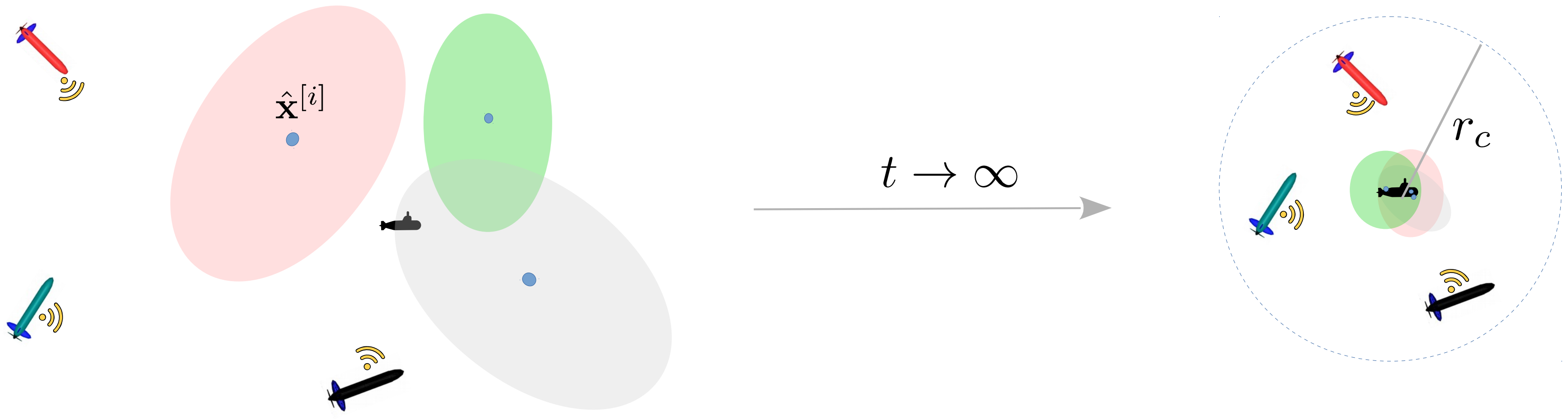
$$\mathbf{x}_{k+1} = \mathbf{f}(\mathbf{x}_k), \quad \mathbf{x}_0 \sim \mathcal{N}(\mathbf{c}_0, P_0)$$

$$\mathbf{q}_k = D\mathbf{x}_k$$

Range measurement model

$$y_k^{[i]} = \left\|\mathbf{p}_k^{[i]} - \mathbf{q}_k\right\| + \eta_k^{[i]}$$

noise



Problem 2 [Cooperative distributed SLAP]

Let $\hat{\mathbf{x}}^{[i]}$ denote an estimate of $\mathbf{x}$ computed by vehicle i. Derive a distributed estimation and control strategy for $\hat{\mathbf{x}}^{[i]}$ and $\mathbf{u}^{[i]} \triangleq \mathrm{col}(\mathbf{v}^{[i]}, \boldsymbol{\omega}^{[i]})$ s.t.

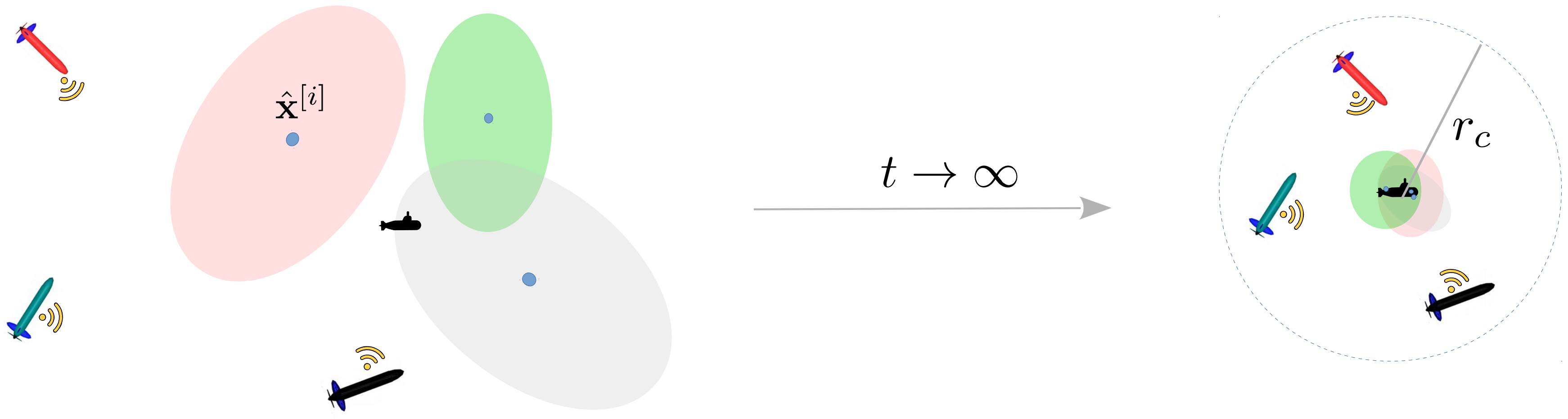
- Cooperative pursuit:

$$\lim_{t\to\infty} \left\|\mathbf{p}^{[i]}(t) - \mathbf{q}(t)\right\| \leq r_c,$$

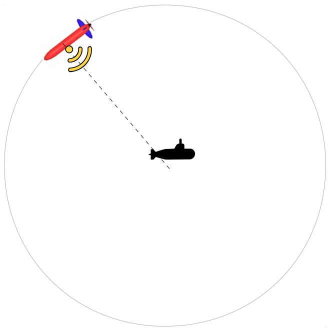
- Cooperative localization:

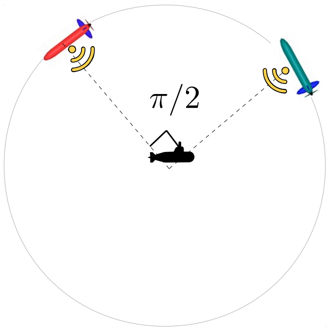
$$\lim_{k\to\infty} \left\|\hat{\mathbf{x}}_k^{[i]} - \mathbf{x}_k\right\| \leq r_e$$

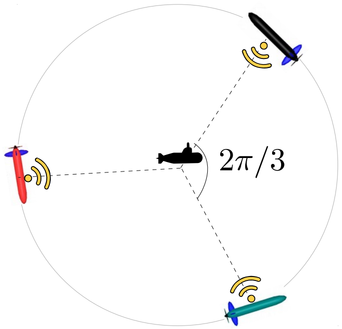
DEC strategy for cooperative SLAP ▷ Problem formulation



"Optimal" vehicles-target relative geometry for target localization purposes [from the MPC approach]

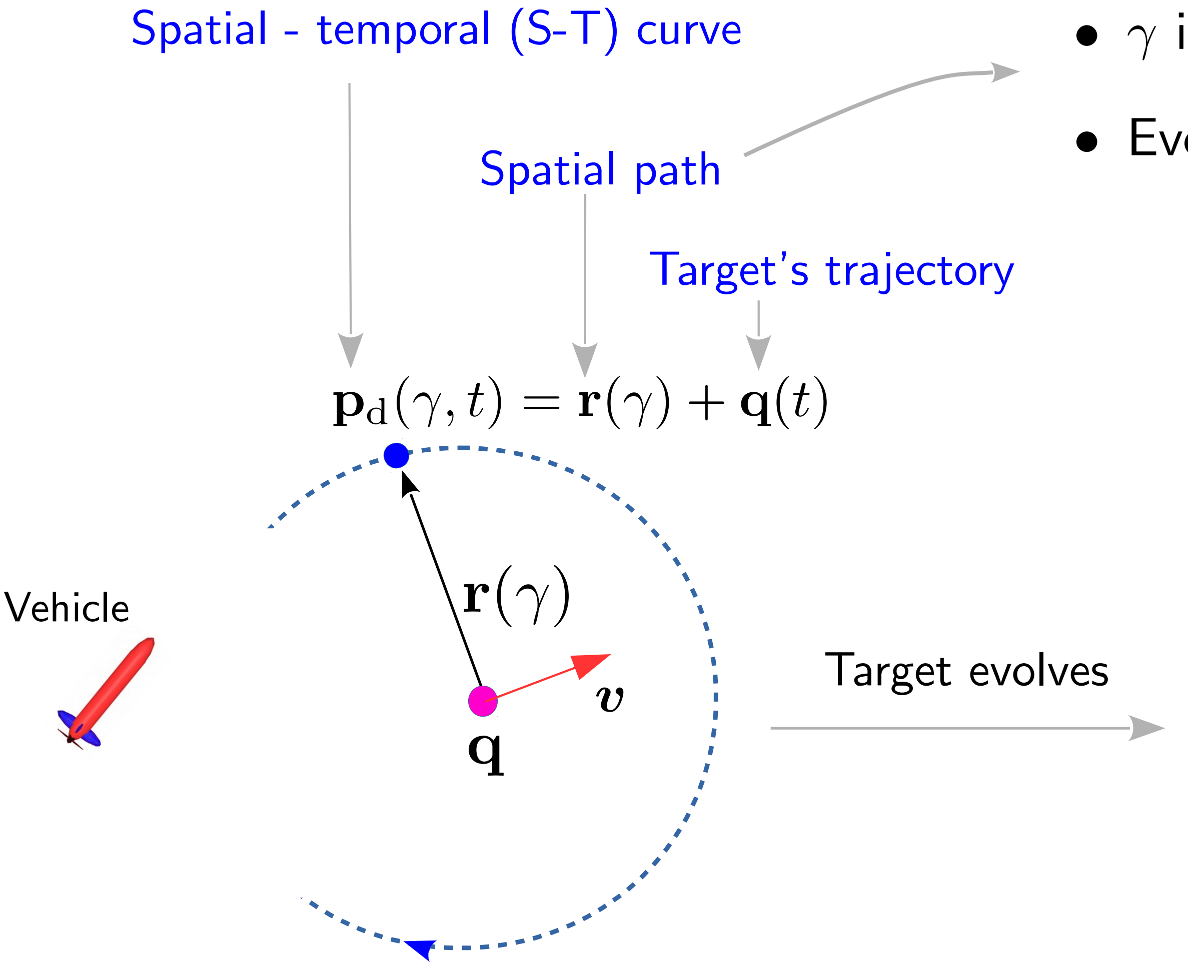


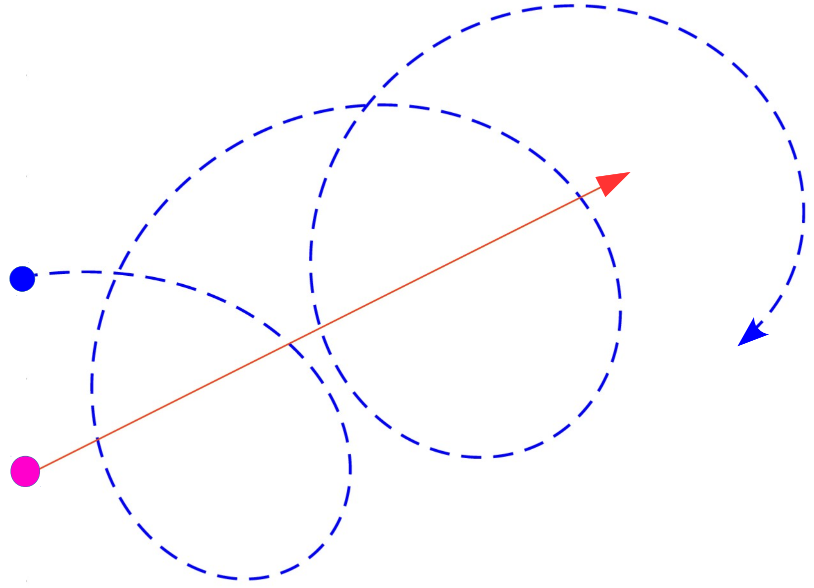




DEC strategy for cooperative SLAP ▷ Trajectory planning

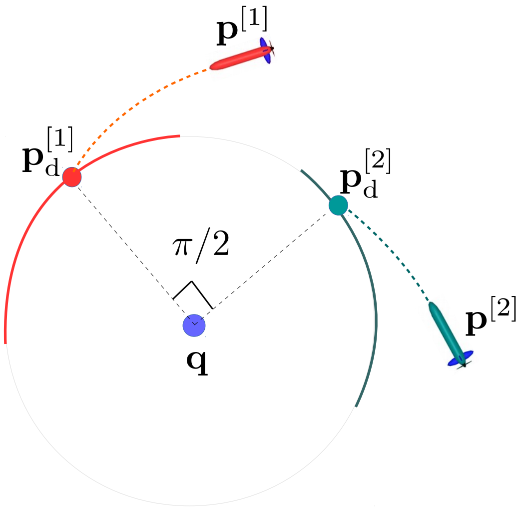
- γ is the parameterizing variable
- Evolution of γ can be chosen freely



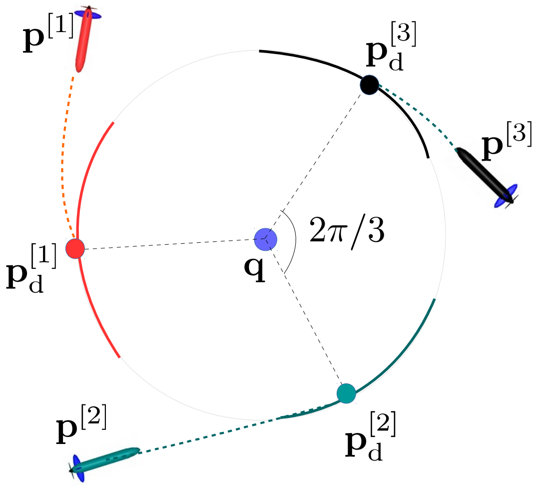


DEC strategy for cooperative SLAP ▷ Desired formation

2 vehicles:



3 vehicles:



Problem 2.1 [Cooperative control for target pursuit]

Derive a distributed estimation and control strategy for $\mathbf{u}^{[i]}$ and $\dot{\gamma}^{[i]}$ s.t.

- Tracking:

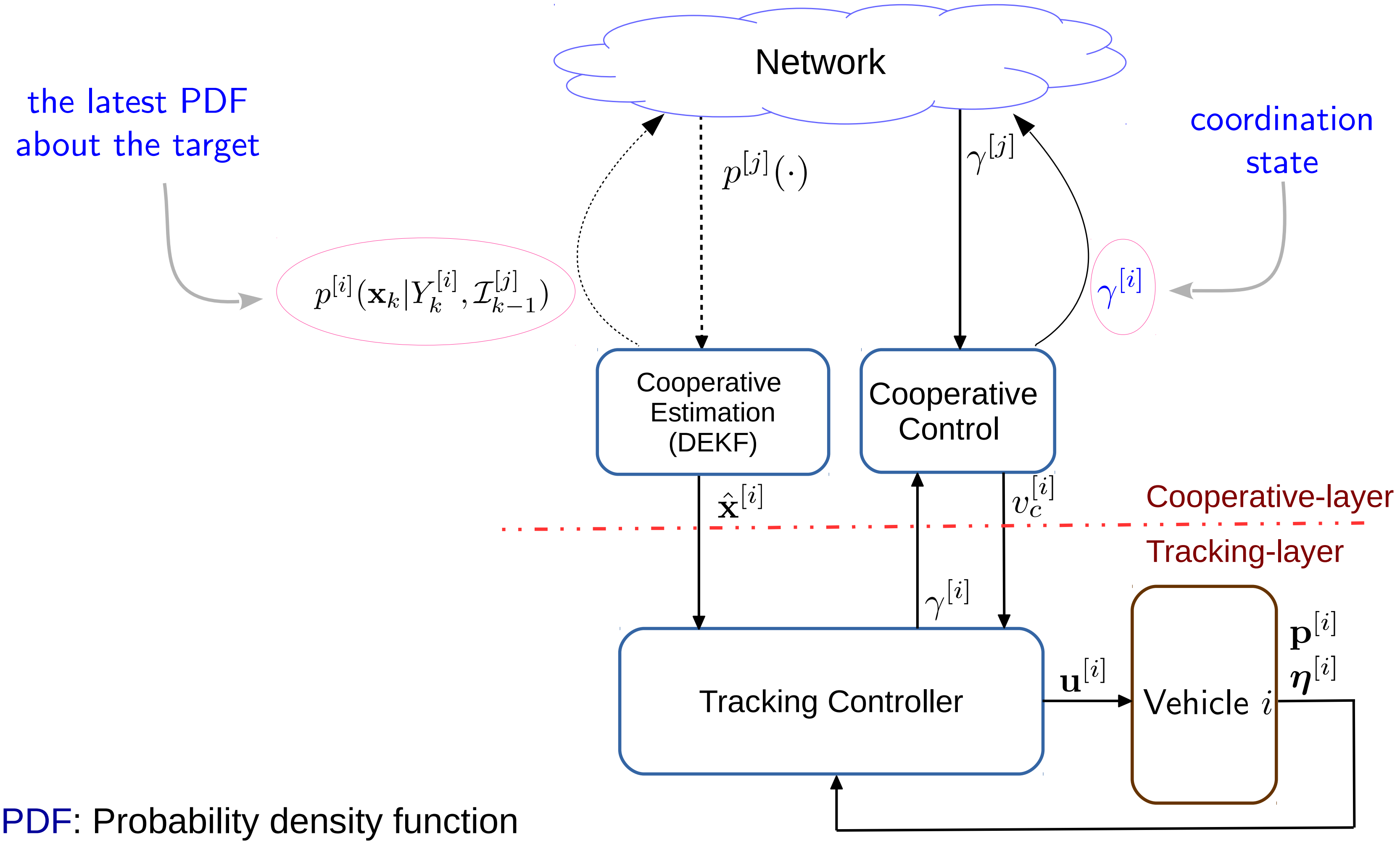
$$\lim_{t\to\infty} \left\| \mathbf{p}^{[i]}(t) - \mathbf{p}_{\mathrm{d}}^{[i]}(t) \right\| \leq \epsilon,$$

- Coordination

$$\lim_{t\to\infty} \gamma^{[i]}(t) - \gamma^{[j]}(t) = 0,$$

$$\lim_{t\to\infty} \dot{\gamma}^{[i]}(t) = \bar{\omega}$$

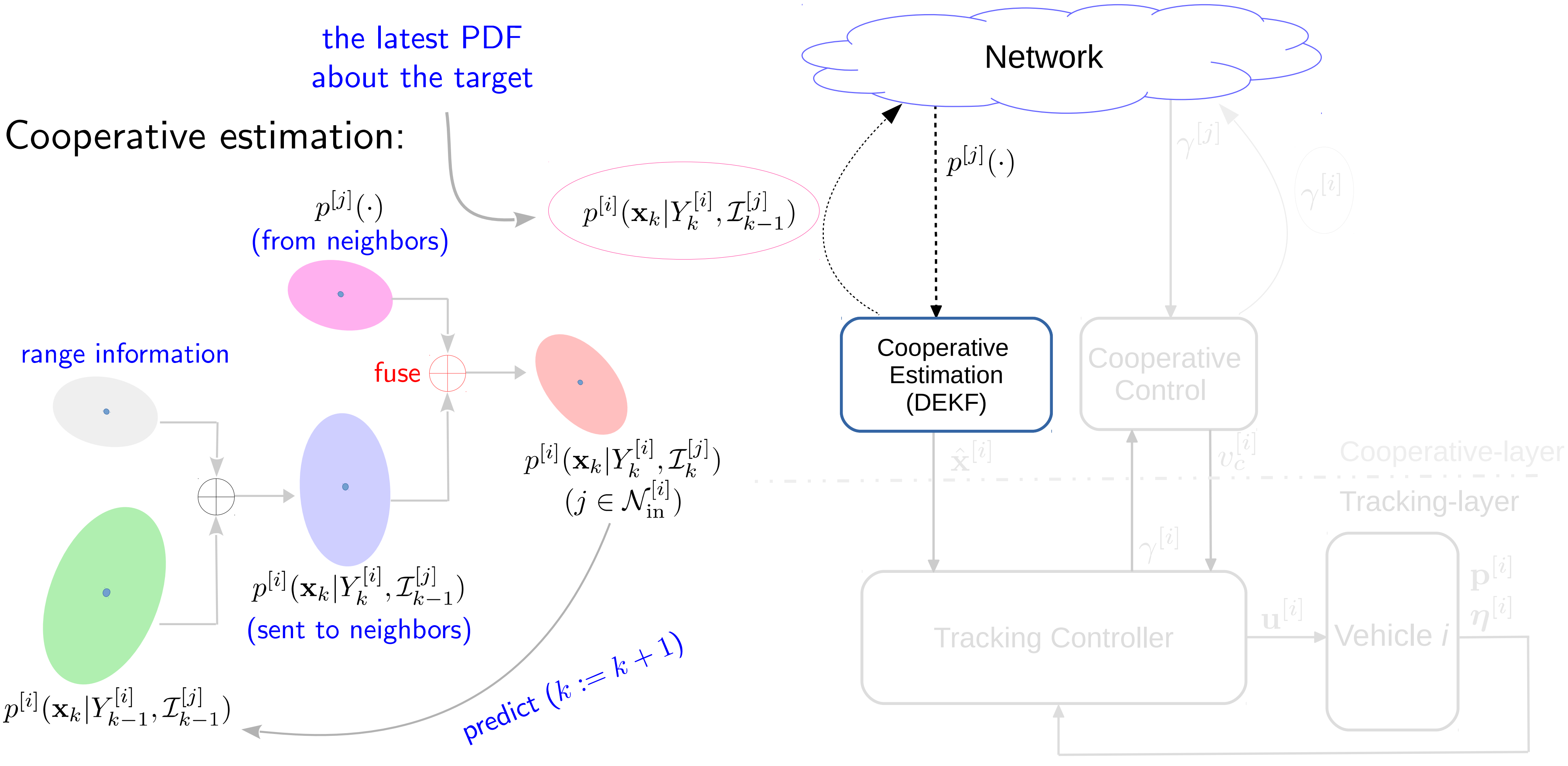
DEC strategy for cooperative SLAP ▷ Proposed DEC architecture



PDF: Probability density function

DEC strategy for cooperative SLAP ▷ Cooperative estimation mechanism

Cooperative estimation:



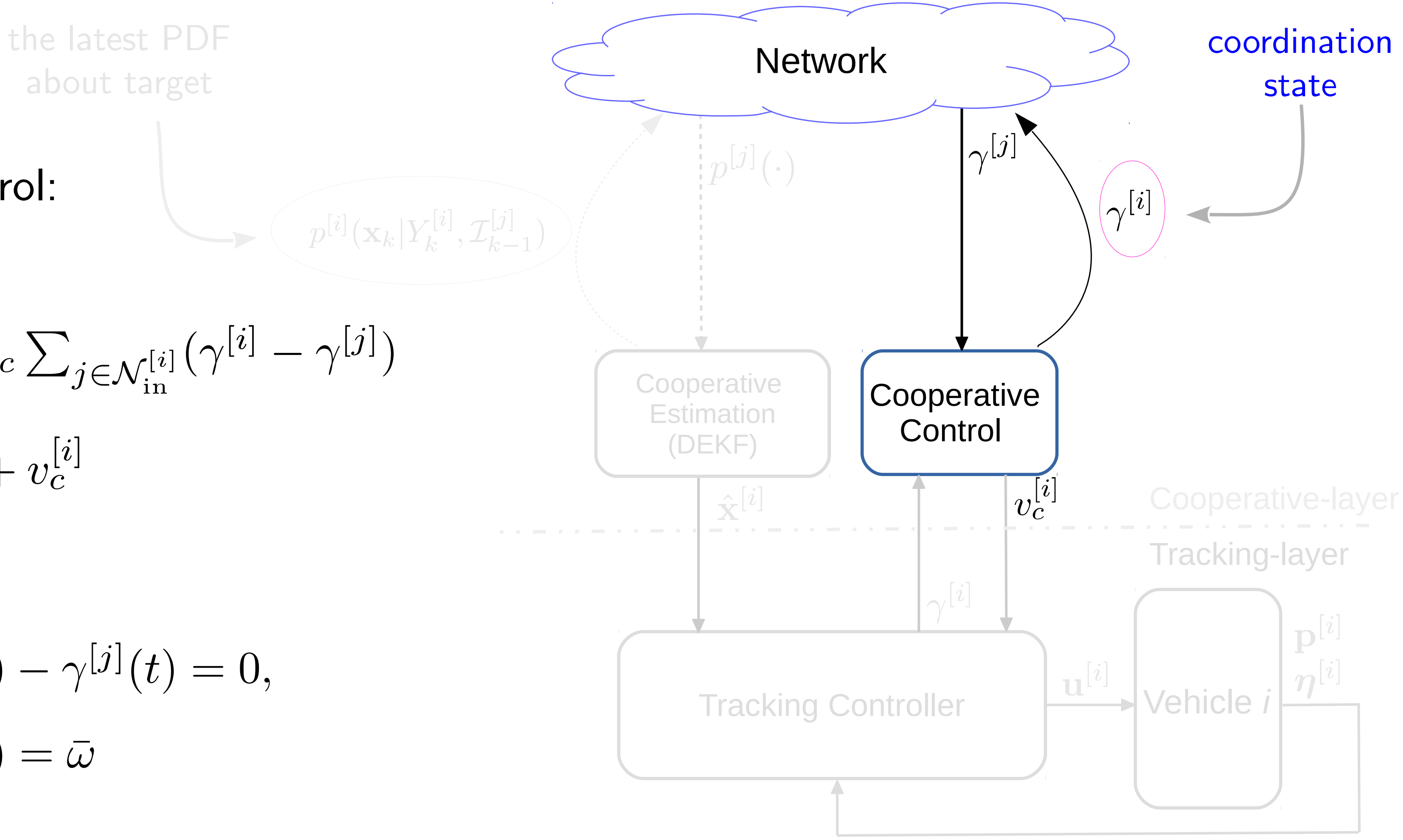
Cooperative control:

$$v_c^{[i]} = -k_c \sum_{j \in \mathcal{N}_{\text{in}}^{[i]}} (\gamma^{[i]} - \gamma^{[j]})$$

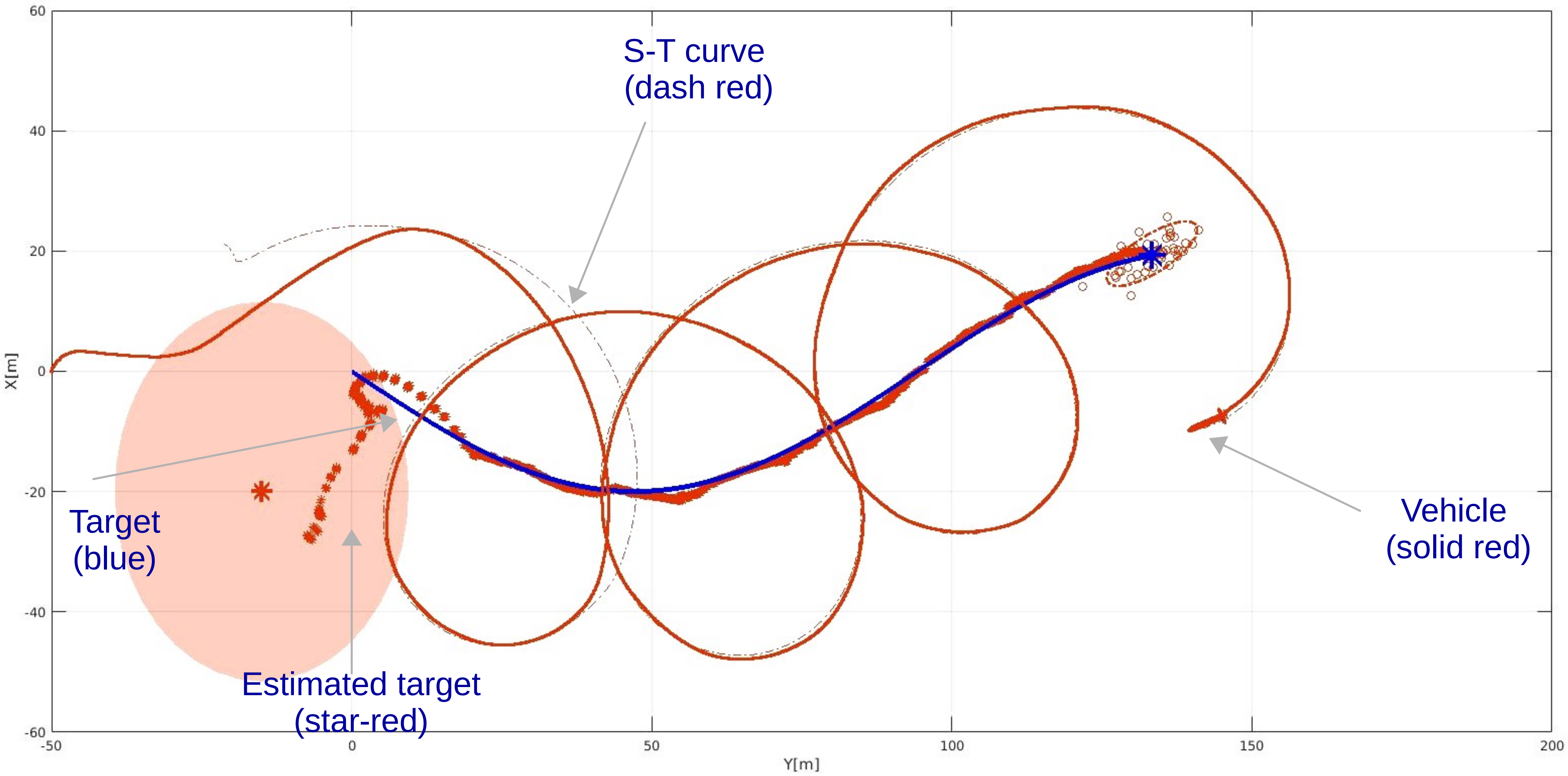
$$\dot{\gamma}^{[i]} = \bar{\omega} + v_c^{[i]}$$

$$\lim_{t\to\infty} \gamma^{[i]}(t) - \gamma^{[j]}(t) = 0,$$

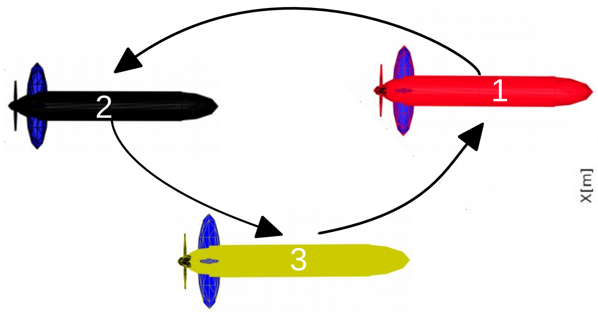
$$\lim_{t\to\infty} \gamma^{[i]}(t) = \bar{\omega}$$

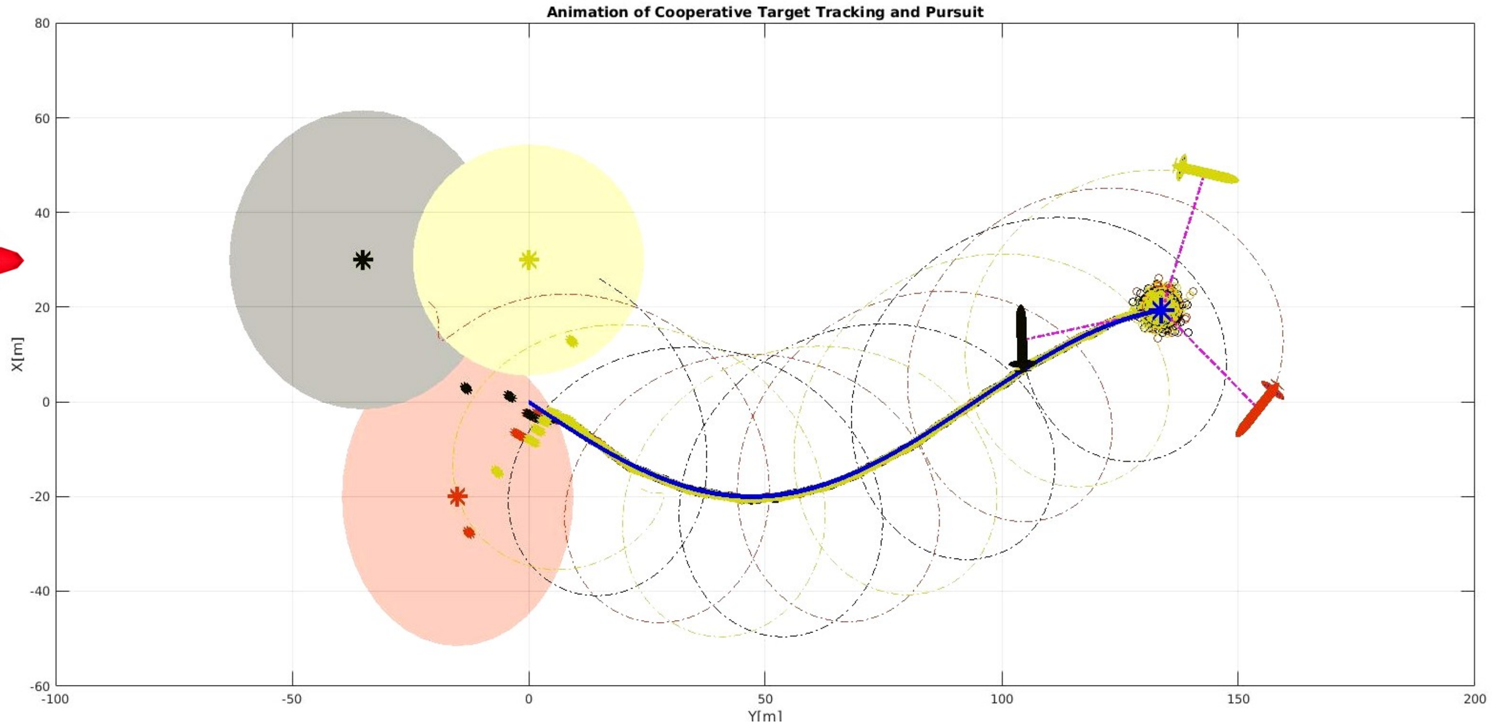


DEC strategy for cooperative SLAP ▷ Simulation with a single vehicle

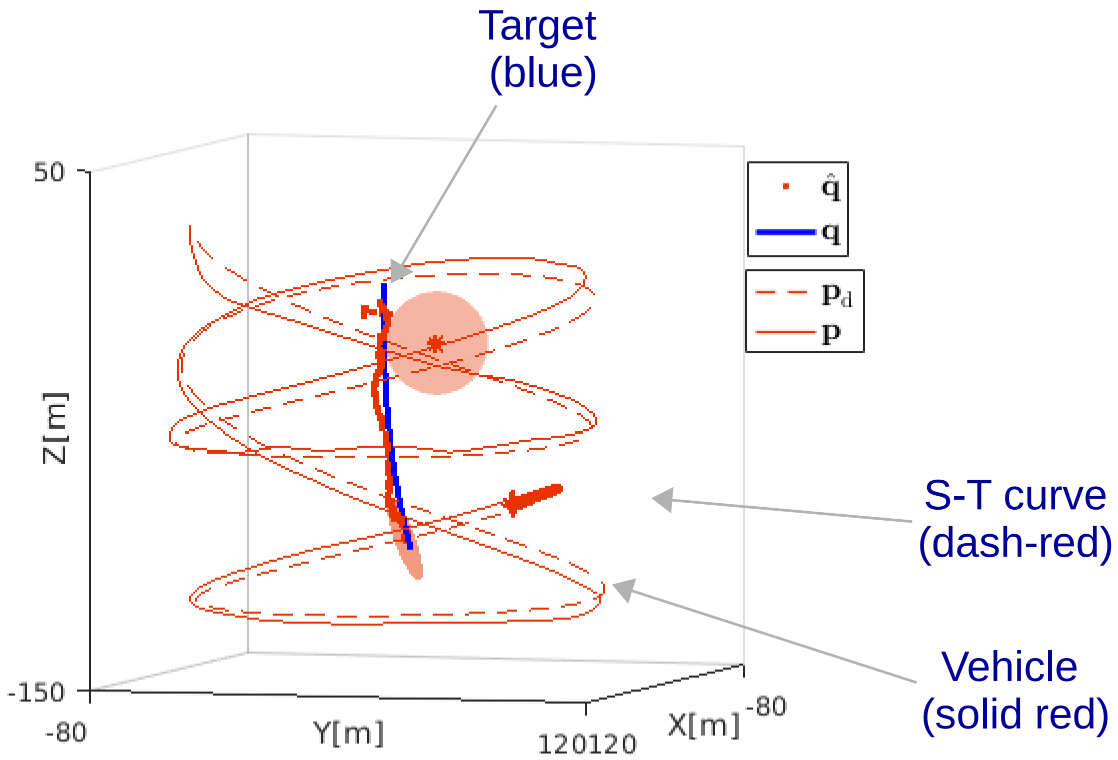


DEC strategy for cooperative SLAP ▷ Simulation with 3 vehicles

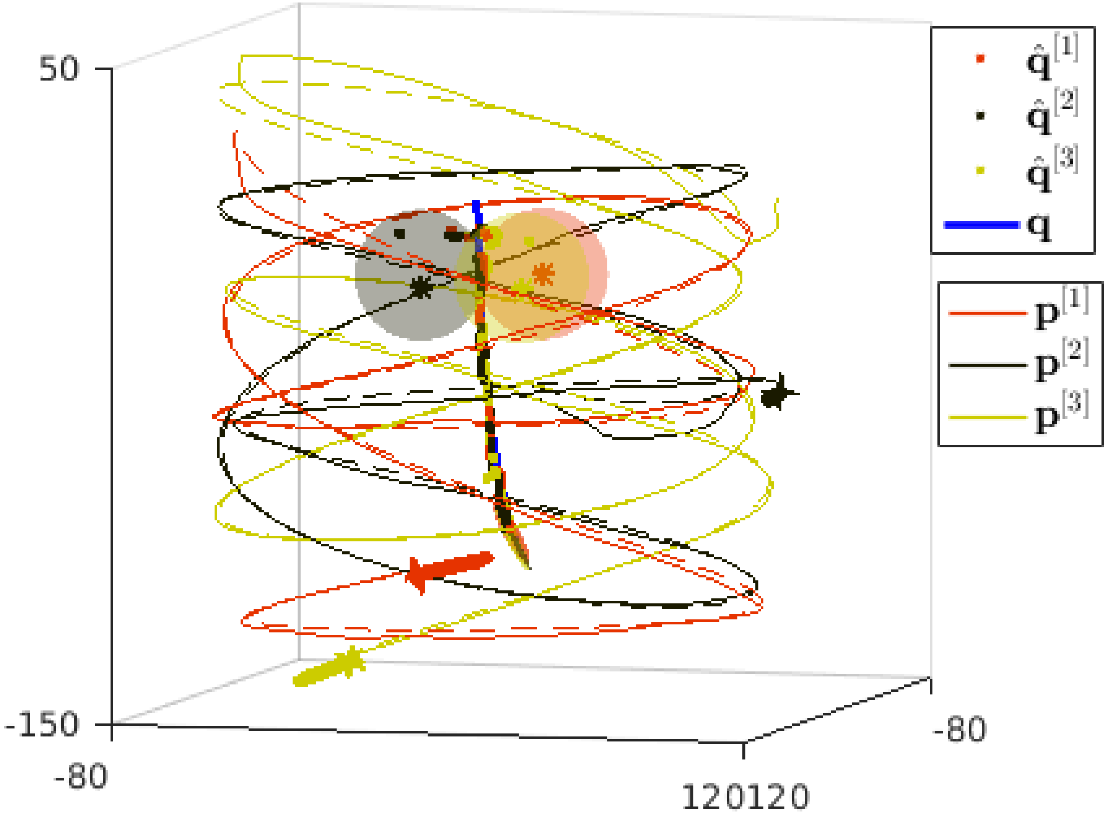




DEC strategy for cooperative SLAP ▷ Simulation with a single vehicle



DEC strategy for cooperative SLAP ▷ Simulation with three vehicle



Summary

Future research directions and plans:

- Extend to the case of multiple targets
- Event driven sampling (measurement strategy)
- Conduct field trials at Expo, Lisbon

Materials about this work can be found at:

https://nt-hung.github.io/research/Range-based-target-localization/

Reference: Nguyen T. Hung, Francisco Rego, Antonio M. Pascoal, “Cooperative distributed estimation and control of multiple autonomous vehicles for range-based underwater target localization and pursuit”, IEEE Transactions on Control Systems and Technology, conditionally accepted with minor revision.

Thank you!

Discussion