

Active Decentralized Scale Estimation for Bearing-Based Localization

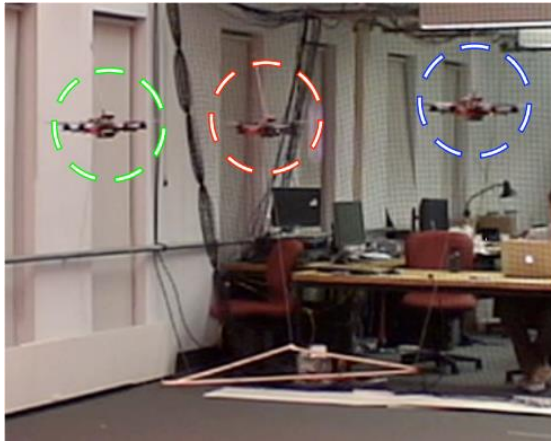
Riccardo Spica, Paolo Robuffo Giordano

Lagadic group

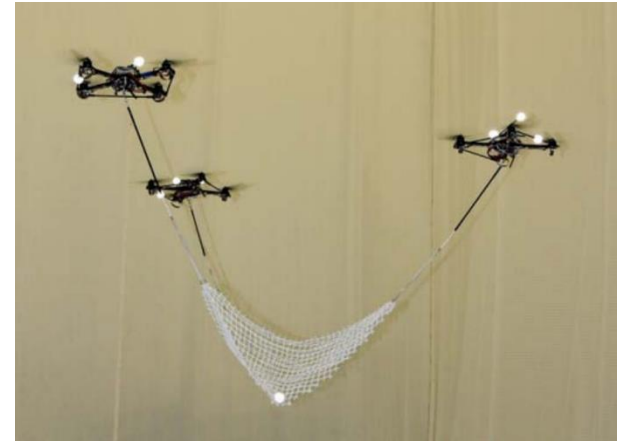
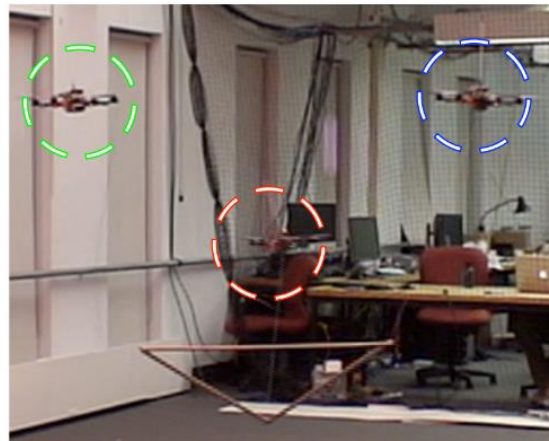
Inria Rennes Bretagne Atlantique & IRISA

<http://www.irisa.fr/lagadic>

Introduction



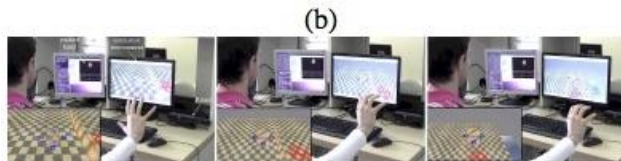
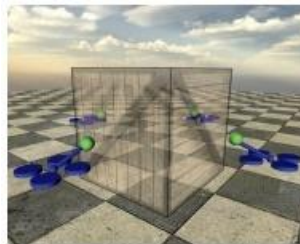
Michael et al. 2011



Ritz et al. 2012



Mellinger et al. 2013



Gioioso et al. 2014



Hausman et al. 2016

Setup

- N UAVs: $q = (p, \psi) \in (\mathbb{R}^3 \times \mathcal{S}^1)^N$

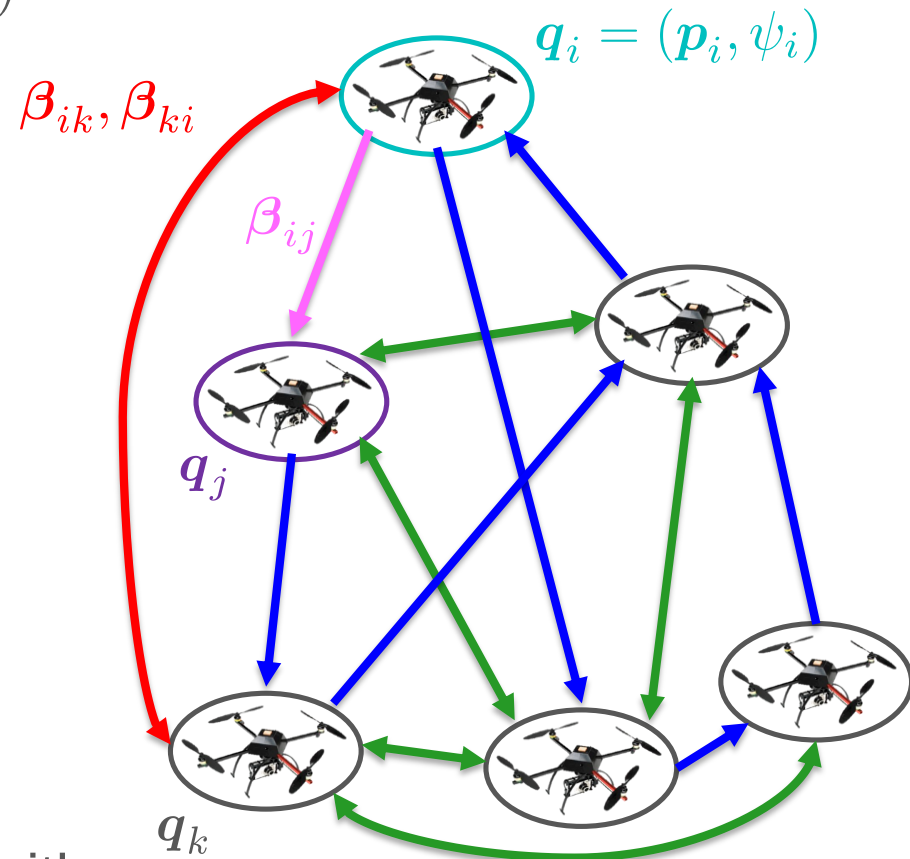
$$\begin{bmatrix} \dot{p}_i \\ \dot{\psi}_i \end{bmatrix} = \begin{bmatrix} R_i(\psi_i) & 0 \\ \mathbf{0} & 1 \end{bmatrix} \begin{bmatrix} u_i \\ w_i \end{bmatrix}$$

- camera** measurements
(if $(i, j) \in \mathcal{E}$)

$$\beta_{ij} = R_i^T \frac{p_j - p_i}{\|p_j - p_i\|} = R_i^T \frac{p_{ij}}{d_{ij}} \in \mathbb{S}^2$$

- directed** measurement **graph**
 $(i, j) \in \mathcal{E} \not\Rightarrow (j, i) \in \mathcal{E}$

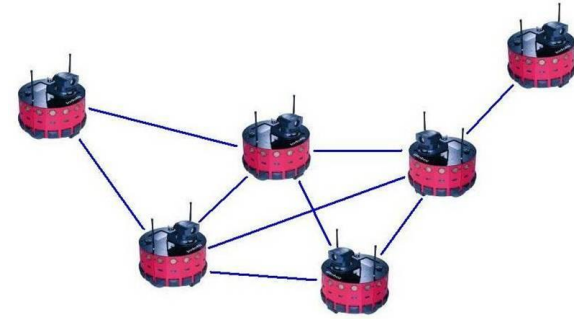
- no** shared reference **frame**
- goal: **decentralized** localization with correct **scale** as **fast** as possible



Control and localization using local measurements

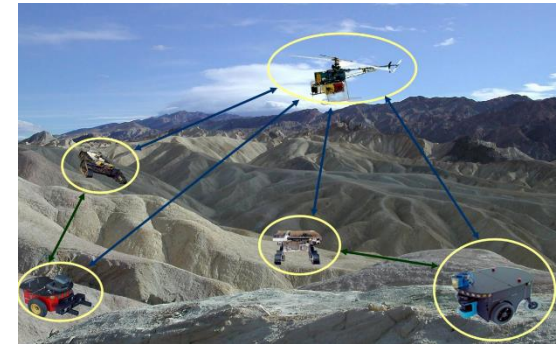
- formation **control**

$$\beta_{ij}(\mathbf{q}) = \beta_{ij}(\mathbf{q}^*), \forall (i, j) \in \mathcal{E} \iff \mathbf{q} \cong \mathbf{q}^*$$



- relative **localization** (in a common frame)

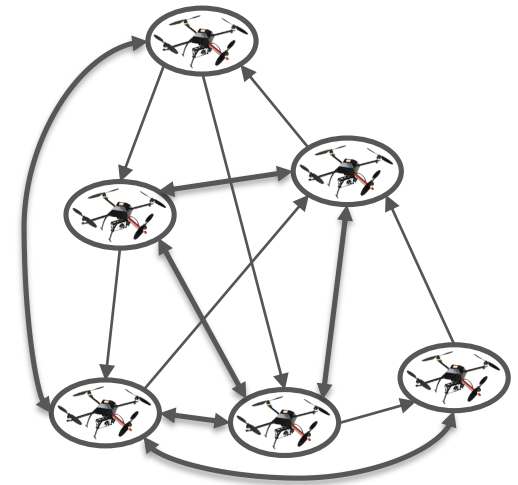
$$\beta_{ij}(\hat{\mathbf{q}}) = \beta_{ij}(\mathbf{q}), \forall (i, j) \in \mathcal{E} \iff \hat{\mathbf{q}} \cong \mathbf{q}$$



- [Anderson et al. 2008; Tron et al. 2015; Montijano et al. 2014; Zelazo et al. 2014/2015]

Bearing rigidity

- **framework** ($\sim$ formation) =
- (measurement) **graph** $\mathcal{G}$ + **configuration** q
- **bearing function** associated to



$$\beta_{\mathcal{G}} : (\mathbb{R}^3 \times \mathcal{S}^1)^N \mapsto (\mathbb{S}^2)^{|\mathcal{E}|}, \quad \beta_{\mathcal{G}}(q) = (\beta e_1, \dots, \beta e_{|\mathcal{E}|})$$

$$\dot{\beta}_{\mathcal{G}} = \frac{\partial \beta_{\mathcal{G}}(q)}{\partial q} \begin{bmatrix} \text{diag}(\mathbf{R}_i) & \mathbf{0} \\ \mathbf{0} & \mathbf{I}_N \end{bmatrix} \begin{bmatrix} u \\ w \end{bmatrix} = \mathcal{B}_{\mathcal{G}}^A(q) \begin{bmatrix} u \\ w \end{bmatrix}$$

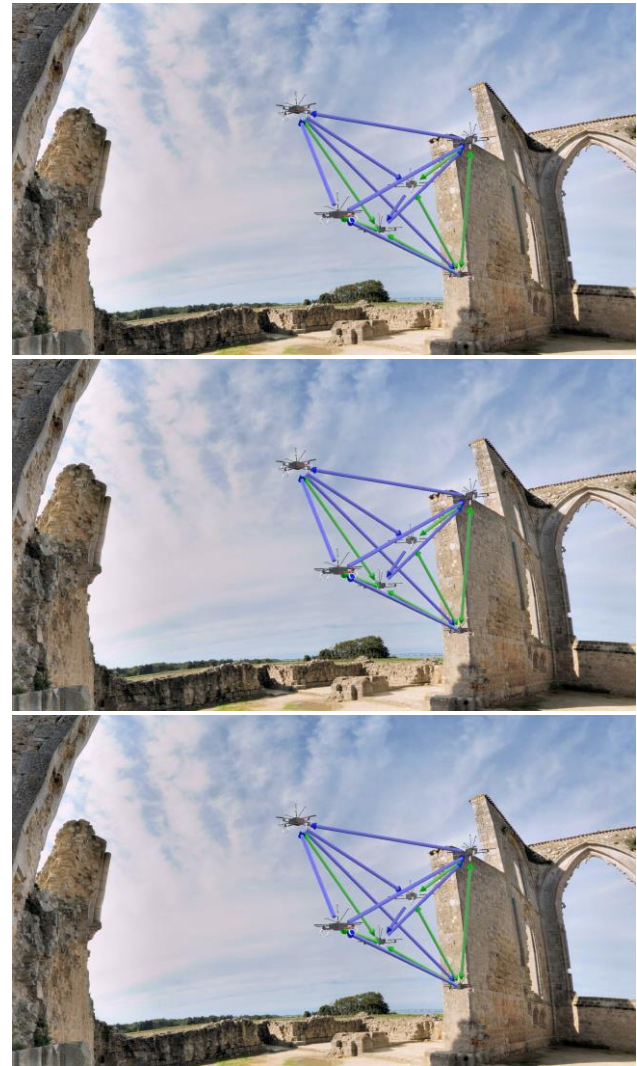
bearing rigidity matrix

- let $\mathcal{K}_N$ be the complete graph, $(\mathcal{G}, q)$ is said to be **infinitesimally bearing rigid** (IBR) if [Anderson et al. 2008]

$\mathcal{N}(\mathcal{B}_{\mathcal{G}}^A(q)) = \mathcal{N}(\mathcal{B}_{\mathcal{K}_N}^A(q)) \Rightarrow$ no need of a complete graph for control/estimation ($O(N)$ vs $O(N^2)$)

Null space transformations for IBR formations

- translation
- rotation around Z
- scaling
 - one (at least) distance measurement can fix the scale [Zelazo et al. 2014]



Bearing-based localization

- $\beta_{\mathcal{G}}(\mathbf{q}) = \text{const}$ $\rightarrow$ if $\mathcal{G}$ is IBR, using $\hat{\mathbf{q}} = k_L \mathcal{B}_{\mathcal{G}}(\hat{\mathbf{q}})^T \beta_{\mathcal{G}}(\mathbf{q})$
$$\hat{\mathbf{q}} \rightarrow \begin{cases} \hat{\mathbf{p}} = s (\mathbf{I}_N \otimes \mathbf{R}(\bar{\psi})) \mathbf{p} + \mathbf{1}_N \otimes t \\ \hat{\psi} = \psi + \mathbf{1}_N \bar{\psi} \end{cases} \quad [\text{Zelazo et al. 2014}]$$

Bearing-based localization

- $\beta_{\mathcal{G}}(\mathbf{q}) = \text{const} \rightarrow$ if $\mathcal{G}$ is IBR, using $\dot{\hat{\mathbf{q}}} = k_L \mathcal{B}_{\mathcal{G}}(\hat{\mathbf{q}})^T \beta_{\mathcal{G}}(\mathbf{q})$

$$\hat{\mathbf{q}} \rightarrow \begin{cases} \hat{\mathbf{p}} = s (\mathbf{I}_N \otimes \mathbf{R}(\bar{\psi})) \mathbf{p} + \mathbf{1}_N \otimes t \\ \hat{\psi} = \psi + \mathbf{1}_N \bar{\psi} \end{cases} \quad [\text{Zelazo et al. 2014}]$$
- $\beta_{\mathcal{G}}(\mathbf{q}) \neq \text{const} \rightarrow$ need **feedforward** $\dot{\beta}_{\mathcal{G}} = \mathcal{B}_{\mathcal{G}}^A(\mathbf{q}) \begin{bmatrix} u \\ w \end{bmatrix}$
 - row block associated to edge (i, j)

$$\begin{bmatrix} \mathbf{0} & -\frac{\mathbf{I}_3 - \beta_{ij}\beta_{ij}^T}{d_{ij}} & \mathbf{0} & \frac{\mathbf{I}_3 - \beta_{ij}\beta_{ij}^T}{d_{ij}} \mathbf{R}_j(\psi_j - \psi_i) & \mathbf{0} & -S\beta_{ij} & \mathbf{0} \end{bmatrix}$$

Bearing-based localization

- $\beta_{\mathcal{G}}(q) = \text{const}$ $\longrightarrow$ if $\mathcal{G}$ is IBR, using $\dot{\hat{q}} = k_L \mathcal{B}_{\mathcal{G}}(\hat{q})^T \beta_{\mathcal{G}}(q)$

$$\hat{q} \rightarrow \begin{cases} \hat{p} = s (\mathbf{I}_N \otimes \mathbf{R}(\bar{\psi})) p + \mathbf{1}_N \otimes t \\ \hat{\psi} = \psi + \mathbf{1}_N \bar{\psi} \end{cases} \quad [\text{Zelazo et al. 2014}]$$

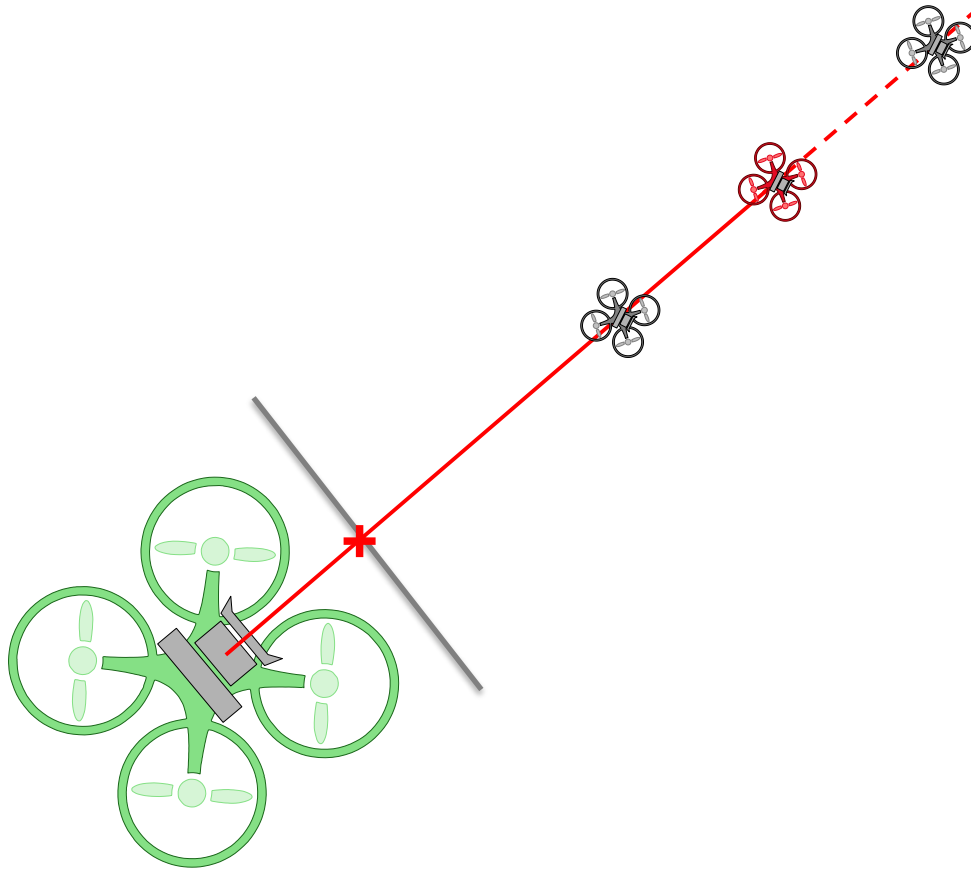
- $\beta_{\mathcal{G}}(q) \neq \text{const}$ $\longrightarrow$ need **feedforward** $\dot{\beta}_{\mathcal{G}} = \mathcal{B}_{\mathcal{G}}^A(q) \begin{bmatrix} u \\ w \end{bmatrix}$
 - row block associated to edge (i, j)

$$\begin{bmatrix} 0 & -\frac{\mathbf{I}_3 - \beta_{ij}\beta_{ij}^T}{\boxed{d_{ij}}} & 0 & \frac{\mathbf{I}_3 - \beta_{ij}\beta_{ij}^T}{\boxed{d_{ij}}} \mathbf{R}_j(\psi_j - \psi_i) & 0 & -S\beta_{ij} & 0 \end{bmatrix}$$

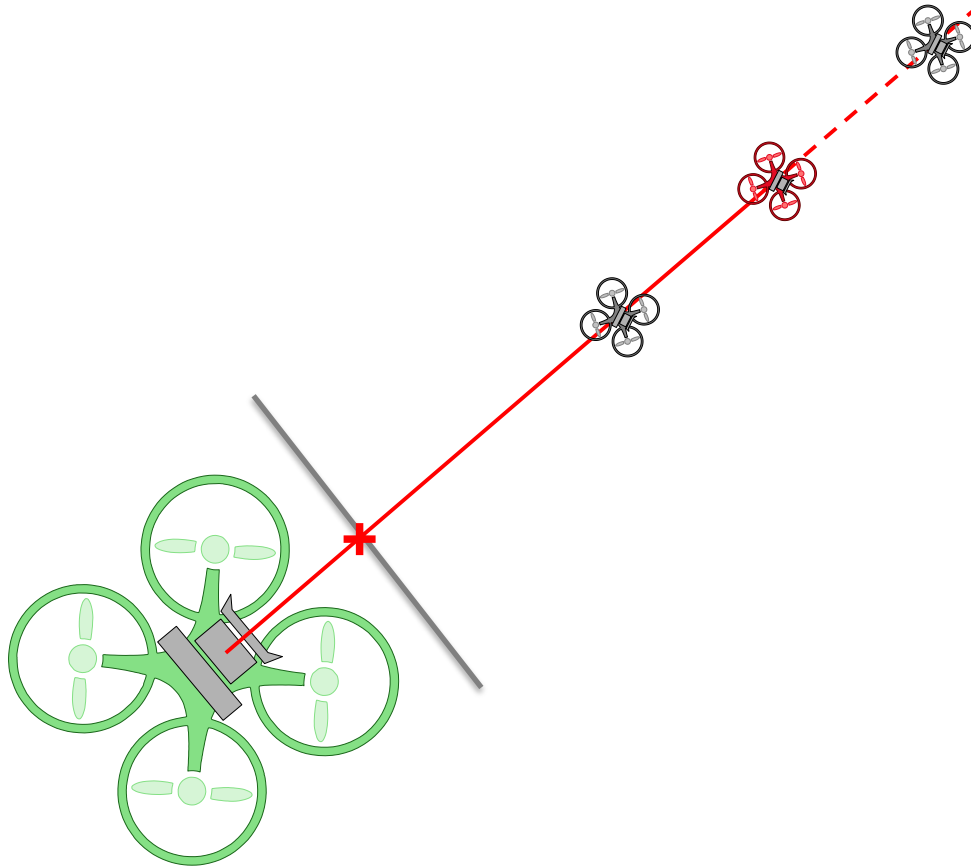
- a **metric** information is needed to recover the **scale**
 - one (at least) “special agent” **measures** its **distance** from a neighbor [Schiano et al. IROS 2016]
 - use the (already known) u to **estimate** relative **distances**

Vision based reconstruction

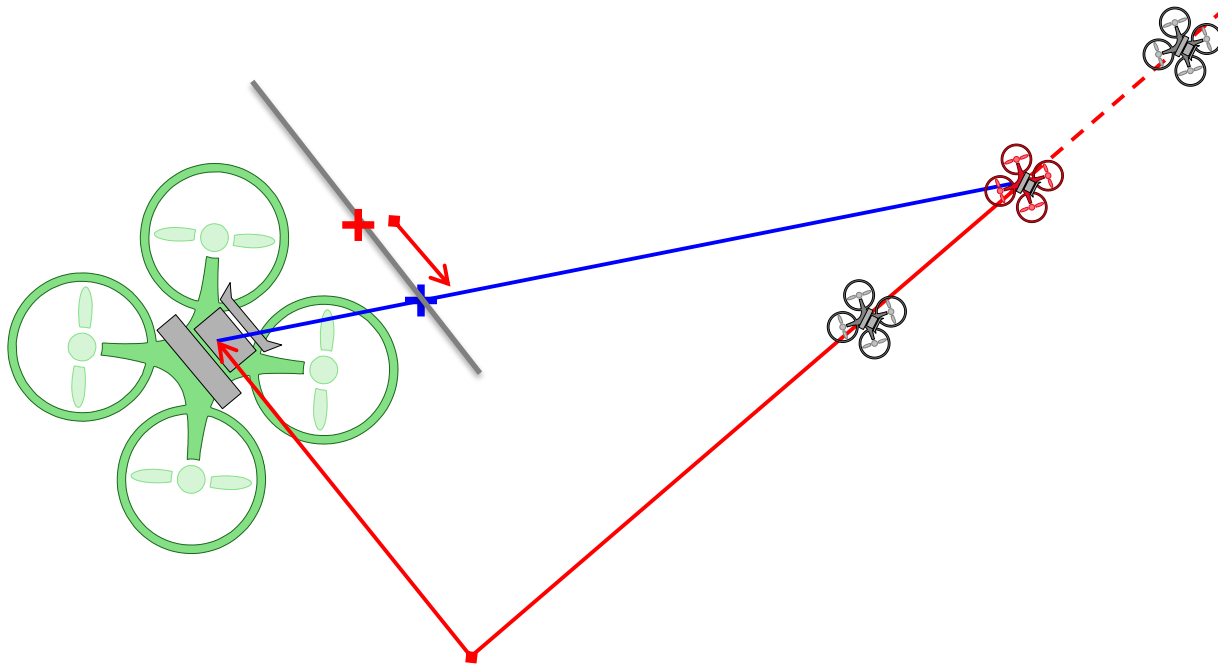
- an inverse problem



Structure from known motion

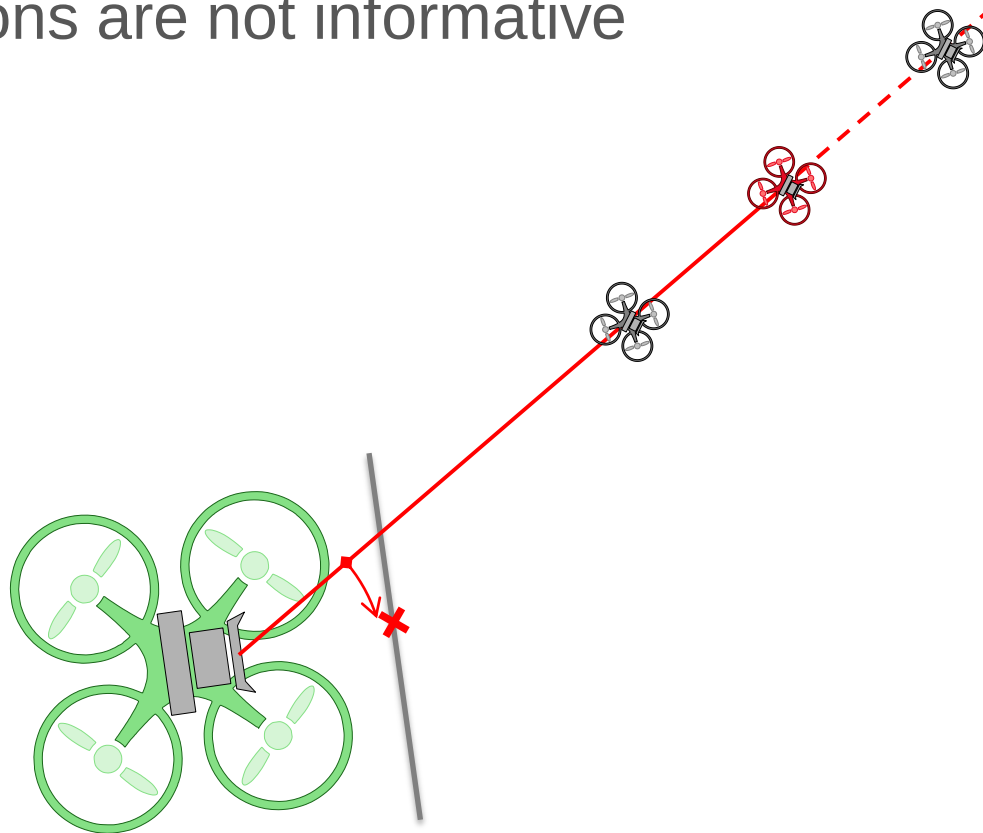


Structure from known motion



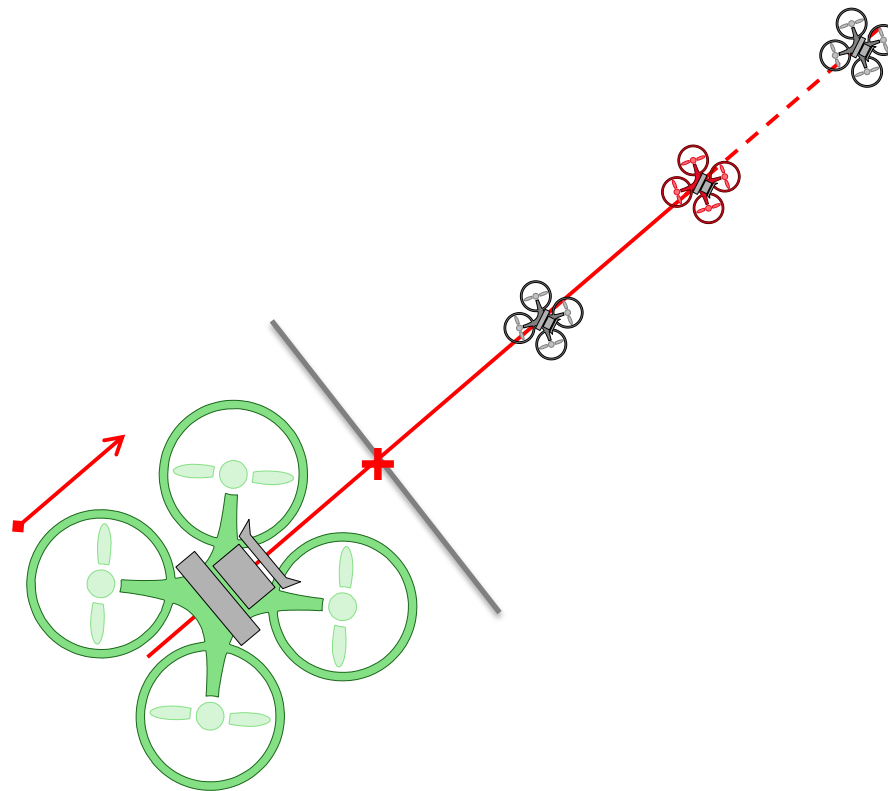
Effects of the camera/agent motion 1/2

- pure rotations are not informative



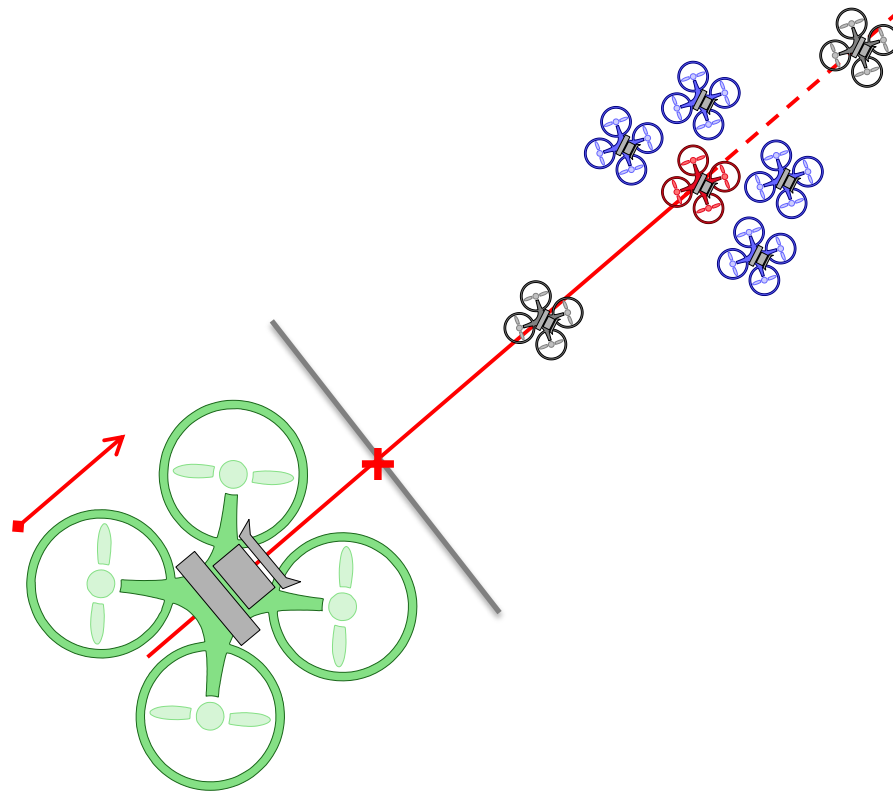
Effects of the camera/agent motion 2/2

- translations along the projection ray are **not informative**



Effects of the camera/agent motion 2/2

- translations along the projection ray are **not informative**
- or **poorly informative**



Distance estimation

- **semi-globally exponentially stable** observer for $\chi_{ij} = 1/d_{ij}$

$$\begin{cases} \dot{\hat{\beta}}_{ij} = -S\beta_{ij}w_i + (I_3 - \beta_{ij}\beta_{ij}^T)u_{ij}\hat{\chi}_{ij} - H(\hat{\beta}_{ij} - \beta_{ij}) \\ \dot{\hat{\chi}}_{ij} = -\hat{\chi}_{ij}^2 u_{ij}^T \beta_{ij} - \alpha u_{ij}^T (I_3 - \beta_{ij}\beta_{ij}^T)(\hat{\beta}_{ij} - \beta_{ij}) \end{cases}$$

where $u_{ij} = {}^iR_j(\psi_j - \psi_i)u_j - u_i$

Distance estimation

- semi-globally exponentially stable observer for $\chi_{ij} = 1/d_{ij}$

$$\begin{cases} \dot{\hat{\beta}}_{ij} = -\mathbf{S}\beta_{ij}w_i + (\mathbf{I}_3 - \beta_{ij}\beta_{ij}^T)\mathbf{u}_{ij}\hat{\chi}_{ij} - \mathbf{H}(\hat{\beta}_{ij} - \beta_{ij}) \\ \dot{\hat{\chi}}_{ij} = -\hat{\chi}_{ij}^2\mathbf{u}_{ij}^T\beta_{ij} - \alpha\mathbf{u}_{ij}^T(\mathbf{I}_3 - \beta_{ij}\beta_{ij}^T)(\hat{\beta}_{ij} - \beta_{ij}) \end{cases}$$

where $\mathbf{u}_{ij} = {}^i\mathbf{R}_j(\psi_j - \psi_i)\mathbf{u}_j - \mathbf{u}_i$

- observer convergence rate depends of

$$\lambda_{ij} = \mathbf{u}_{ij}^T(\mathbf{I}_3 - \beta_{ij}\beta_{ij}^T)\mathbf{u}_{ij}$$

Distance estimation

- semi-globally exponentially stable observer for $\chi_{ij} = 1/d_{ij}$

$$\begin{cases} \dot{\hat{\beta}}_{ij} = -\mathbf{S}\beta_{ij}w_i + (\mathbf{I}_3 - \beta_{ij}\beta_{ij}^T)\mathbf{u}_{ij}\hat{\chi}_{ij} - \mathbf{H}(\hat{\beta}_{ij} - \beta_{ij}) \\ \dot{\hat{\chi}}_{ij} = -\hat{\chi}_{ij}^2\mathbf{u}_{ij}^T\beta_{ij} - \alpha\mathbf{u}_{ij}^T(\mathbf{I}_3 - \beta_{ij}\beta_{ij}^T)(\hat{\beta}_{ij} - \beta_{ij}) \end{cases}$$

where $\mathbf{u}_{ij} = {}^i\mathbf{R}_j(\psi_j - \psi_i)\mathbf{u}_j - \mathbf{u}_i$

- observer convergence rate depends of

$$\lambda_{ij} = \mathbf{u}_{ij}^T(\mathbf{I}_3 - \beta_{ij}\beta_{ij}^T)\mathbf{u}_{ij} \longrightarrow \mathbf{u}_{ij} = \arg \max\{\lambda_{ij}(\mathbf{u}_{ij})\}$$

Distance estimation

- semi-globally exponentially stable observer for $\chi_{ij} = 1/d_{ij}$

$$\begin{cases} \dot{\hat{\beta}}_{ij} = -\mathbf{S}\beta_{ij}w_i + (\mathbf{I}_3 - \beta_{ij}\beta_{ij}^T)\mathbf{u}_{ij}\hat{\chi}_{ij} - \mathbf{H}(\hat{\beta}_{ij} - \beta_{ij}) \\ \dot{\hat{\chi}}_{ij} = -\hat{\chi}_{ij}^2\mathbf{u}_{ij}^T\beta_{ij} - \alpha\mathbf{u}_{ij}^T(\mathbf{I}_3 - \beta_{ij}\beta_{ij}^T)(\hat{\beta}_{ij} - \beta_{ij}) \end{cases}$$

where $\mathbf{u}_{ij} = {}^i\mathbf{R}_j(\psi_j - \psi_i)\mathbf{u}_j - \mathbf{u}_i$

- observer convergence rate depends of

$$\lambda_{ij} = \mathbf{u}_{ij}^T(\mathbf{I}_3 - \beta_{ij}\beta_{ij}^T)\mathbf{u}_{ij} \longrightarrow \mathbf{u}_{ij} = \arg \max\{\lambda_{ij}(\mathbf{u}_{ij})\}$$

- convergence of $\hat{\chi}_{ij}$ to χ_{ij} can be detected by measuring

$$E_{ij}(t) = \frac{1}{T} \int_{t-T}^t \|\hat{\beta}_{ij}(\tau) - \beta_{ij}(\tau)\|^2 d\tau = 0 \Leftrightarrow \hat{\chi}_{ij} - \chi_{ij} = 0$$

R. Spica, P. Robuffo Giordano, F. Chaumette, "Active Structure from Motion: Application to Point, Sphere and Cylinder." IEEE Trans. on Robotics, vol. 30, no. 6, pp. 5434-5440, 2014.

Distance estimation

- semi-globally exponentially stable observer for $\chi_{ij} = 1/d_{ij}$

$$\begin{cases} \dot{\hat{\beta}}_{ij} = -\mathbf{S}\beta_{ij}w_i + (\mathbf{I}_3 - \beta_{ij}\beta_{ij}^T)\mathbf{u}_{ij}\hat{\chi}_{ij} - \mathbf{H}(\hat{\beta}_{ij} - \beta_{ij}) \\ \dot{\hat{\chi}}_{ij} = -\hat{\chi}_{ij}^2\mathbf{u}_{ij}^T\beta_{ij} - \alpha\mathbf{u}_{ij}^T(\mathbf{I}_3 - \beta_{ij}\beta_{ij}^T)(\hat{\beta}_{ij} - \beta_{ij}) \end{cases}$$

where $\mathbf{u}_{ij} = {}^i\mathbf{R}_j(\psi_j - \psi_i)\mathbf{u}_j - \mathbf{u}_i$ not known in general!

- observer convergence rate depends of

$$\lambda_{ij} = \mathbf{u}_{ij}^T(\mathbf{I}_3 - \beta_{ij}\beta_{ij}^T)\mathbf{u}_{ij} \longrightarrow \mathbf{u}_{ij} = \arg \max\{\lambda_{ij}(\mathbf{u}_{ij})\}$$

- convergence of $\hat{\chi}_{ij}$ to χ_{ij} can be detected by measuring

$$E_{ij}(t) = \frac{1}{T} \int_{t-T}^t \|\hat{\beta}_{ij}(\tau) - \beta_{ij}(\tau)\|^2 d\tau = 0 \Leftrightarrow \hat{\chi}_{ij} - \chi_{ij} = 0$$

R. Spica, P. Robuffo Giordano, F. Chaumette, "Active Structure from Motion: Application to Point, Sphere and Cylinder." IEEE Trans. on Robotics, vol. 30, no. 6, pp. 5434-5440, 2014.

Relative orientation

- no common frame of reference

 $\psi_{ij} = \psi_j - \psi_i$ not directly known in general

Relative orientation

- no common frame of reference

 $\psi_{ij} = \psi_j - \psi_i$ not directly known in general

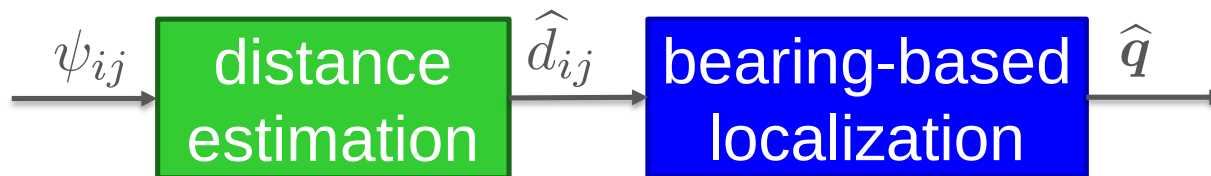
- however for **reciprocal links** $(i, j) \in \mathcal{E}, (j, i) \in \mathcal{E}$
 - $\beta_{ij} = -{}^iR_j(\psi_{ij})\beta_{ji} \Rightarrow \psi_{ij} = \text{atan2}(\|\beta_{ji} \times \beta_{ij}\|, -\beta_{ij}^T \beta_{ji})$
 - β_{ij}, β_{ji} can be exchanged over **local communication**

Relative orientation

- no common frame of reference

 $\psi_{ij} = \psi_j - \psi_i$ not directly known in general

- however for **reciprocal links** $(i, j) \in \mathcal{E}, (j, i) \in \mathcal{E}$
 - $\beta_{ij} = -{}^iR_j(\psi_{ij})\beta_{ji} \Rightarrow \psi_{ij} = \text{atan2}(\|\beta_{ji} \times \beta_{ij}\|, -\beta_{ij}^T \beta_{ji})$
 - β_{ij}, β_{ji} can be exchanged over **local communication**
- u_{ij} is known for reciprocal links and d_{ij} can be estimated for all these links  need **at least one reciprocal link** (i.e. a pair of agents in mutual visibility)



Unconstrained active estimation

- the **estimation** of the formation scale is the **primary** task

$$\dot{\mathbf{u}}_i = \underbrace{-\frac{k_\nu}{2} \frac{\nu_i - \nu^*}{\nu_i} \mathbf{u}_i}_{\text{constant } \|\mathbf{u}_i\|} + k_{\bar{\lambda}} \underbrace{\left(\mathbf{I}_3 - \frac{\mathbf{u}_i \mathbf{u}_i^T}{2\nu_i} \right)}_{\text{projector}} \underbrace{\nabla_{\mathbf{u}_i} \bar{\lambda}}_{\text{excitation}}$$

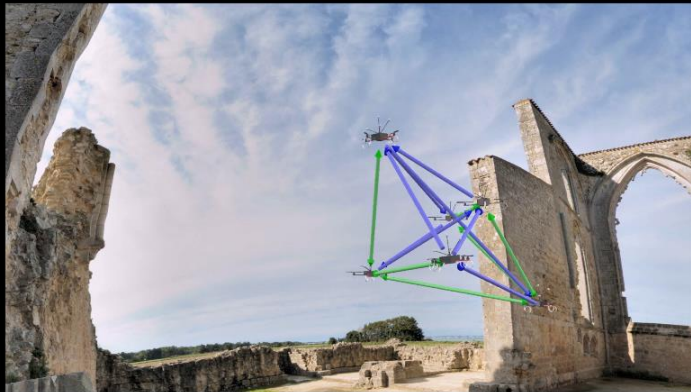
$$\nu_i = \frac{1}{2} \mathbf{u}_i^T \mathbf{u}_i \quad \lambda_{ij} = \mathbf{u}_{ij}^T (\mathbf{I}_3 - \beta_{ij} \beta_{ij}^T) \mathbf{u}_{ij}$$

$$\bar{\lambda} = \sqrt[p]{\sum_{(i,j) \in \mathcal{E}_u} \lambda_{ij}^p} \xrightarrow{p \ll 0} \min_{(i,j)} \lambda_{ij} \quad (\text{worst case})$$

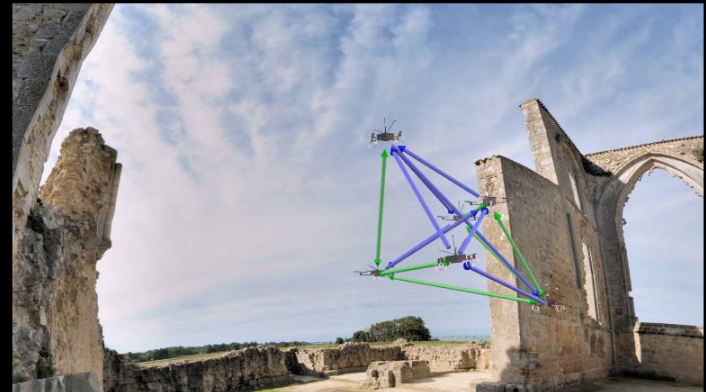
- average **consensus** can be used to estimate $\bar{\lambda}$ in a **decentralized** way

Simulations of unconstrained active estimation

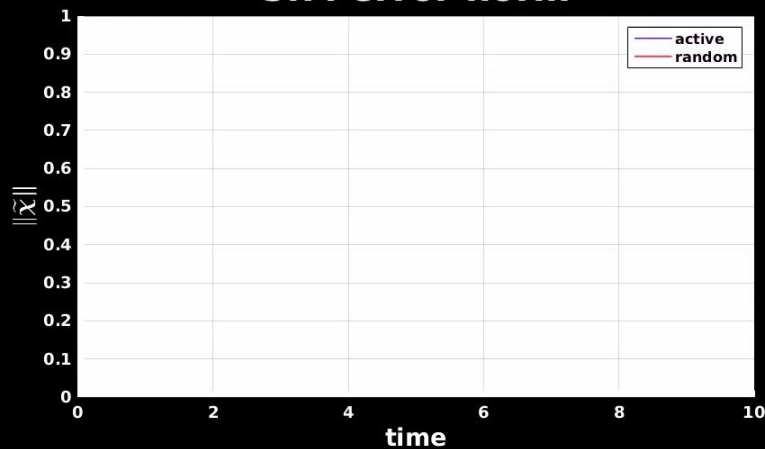
Active SfM optimization



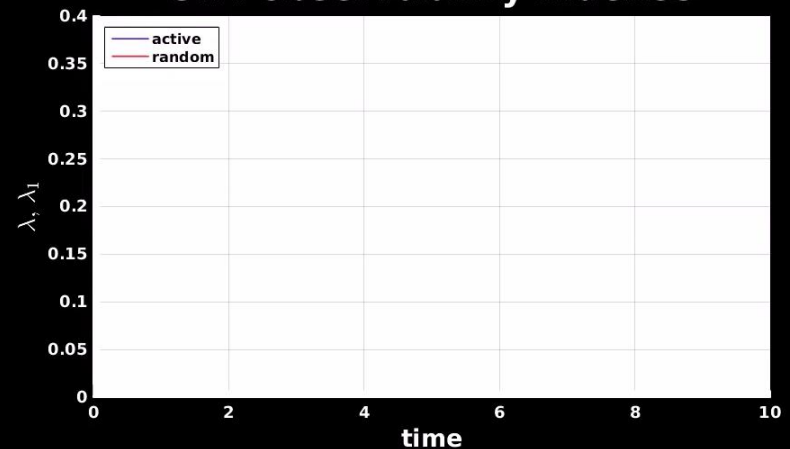
Random motion



SfM error norm



SfM observability indexes



R. Spica, and P. Robuffo Giordano, "Active Decentralized Scale Estimation for Bearing-Based Localization," In IEEE/RSJ IROS 2016, Daejeon, Korea, October 2016.

Bearing-constrained active perception

- observability maximization must be done while maintaining a **desired** bearing (IBR) **formation**

$$\begin{cases} u_i = \dot{u}_i^F \\ w_i = \dot{w}_i^F \end{cases} + \mathcal{N}(\mathcal{B}_{\mathcal{K}_N}^A(q))$$

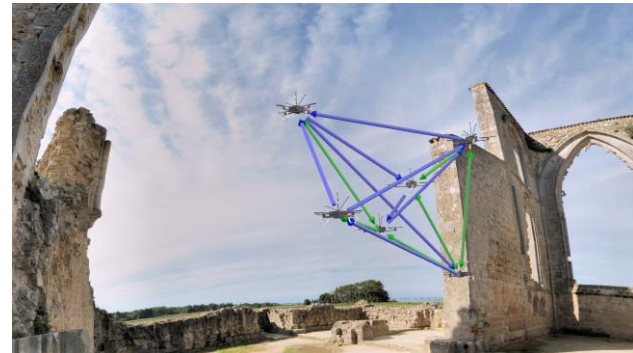
formation control
[Schiano et al. 2016]

observability maximization
in the null space of
the bearing constraints

Null space motions $\lambda_{ij} = \mathbf{u}_{ij}^T (\mathbf{I}_3 - \boldsymbol{\beta}_{ij} \boldsymbol{\beta}_{ij}^T) \mathbf{u}_{ij}$

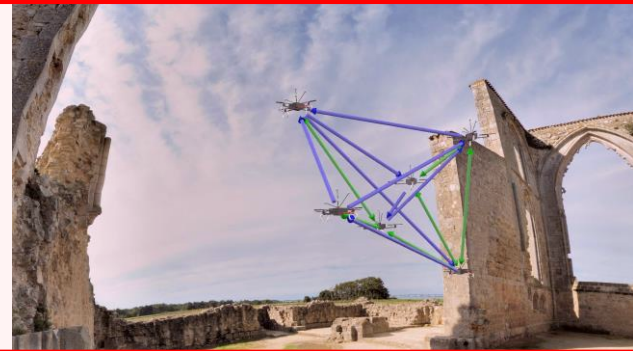
- translation

$$\mathbf{u}_{ij} = \mathbf{0} \implies \lambda_{ij} = 0$$



- rotation around Z

$$\lambda_{ij} \neq 0$$



- scaling

$$\mathbf{u}_{ij} \parallel \boldsymbol{\beta}_{ij} \implies \lambda_{ij} = 0$$

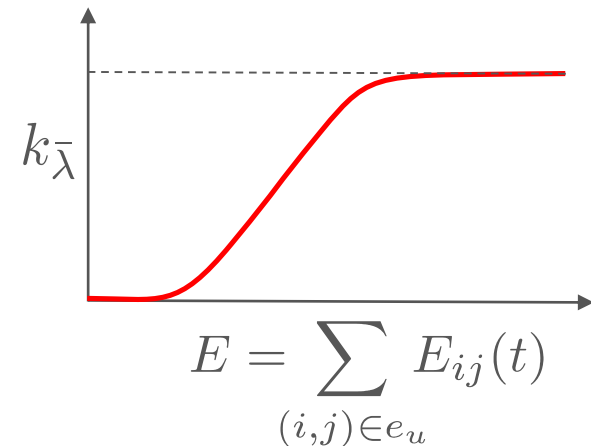


Bearing-constrained active perception

- observability maximization must be done while maintaining a **desired bearing formation**

$$\begin{cases} \mathbf{u}_i = \mathbf{u}_i^F + w_{\bar{\lambda}} \mathbf{R}_i^T \mathbf{S}(\mathbf{p}_i - \bar{\mathbf{p}}) \\ w_i = w_i^F + w_{\bar{\lambda}} \end{cases}$$

$$\dot{w}_{\bar{\lambda}} \propto k_{\bar{\lambda}}(E) \frac{\partial \bar{\lambda}}{\partial w_{\bar{\lambda}}}^T$$

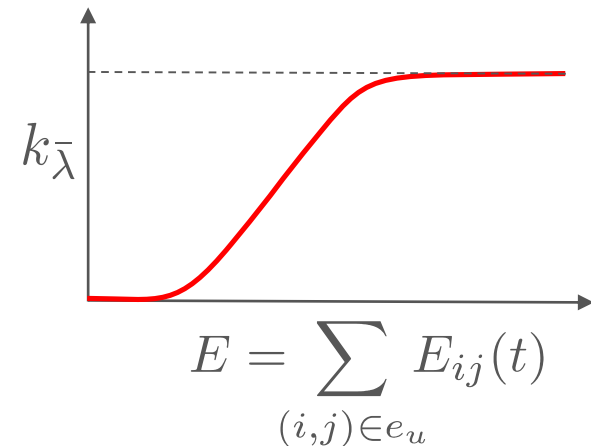


Bearing-constrained active perception

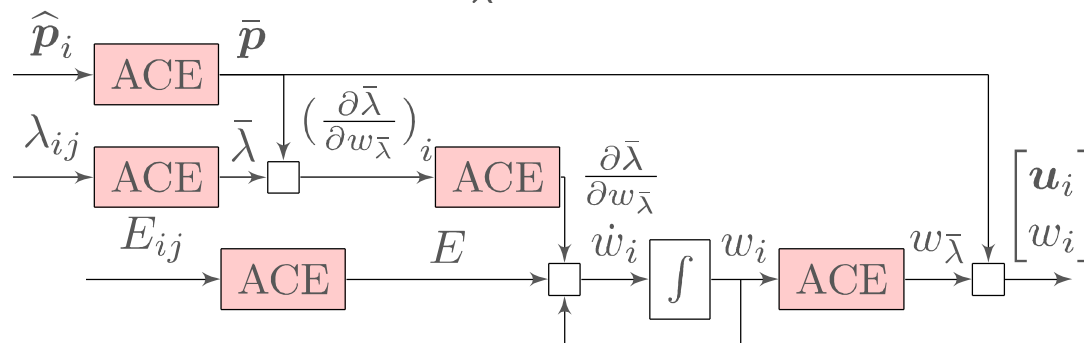
- observability maximization must be done while maintaining a **desired bearing formation**

$$\begin{cases} \mathbf{u}_i = \mathbf{u}_i^F + w_{\bar{\lambda}} \mathbf{R}_i^T \mathbf{S}(\mathbf{p}_i - \bar{\mathbf{p}}) \\ w_i = w_i^F + w_{\bar{\lambda}} \end{cases}$$

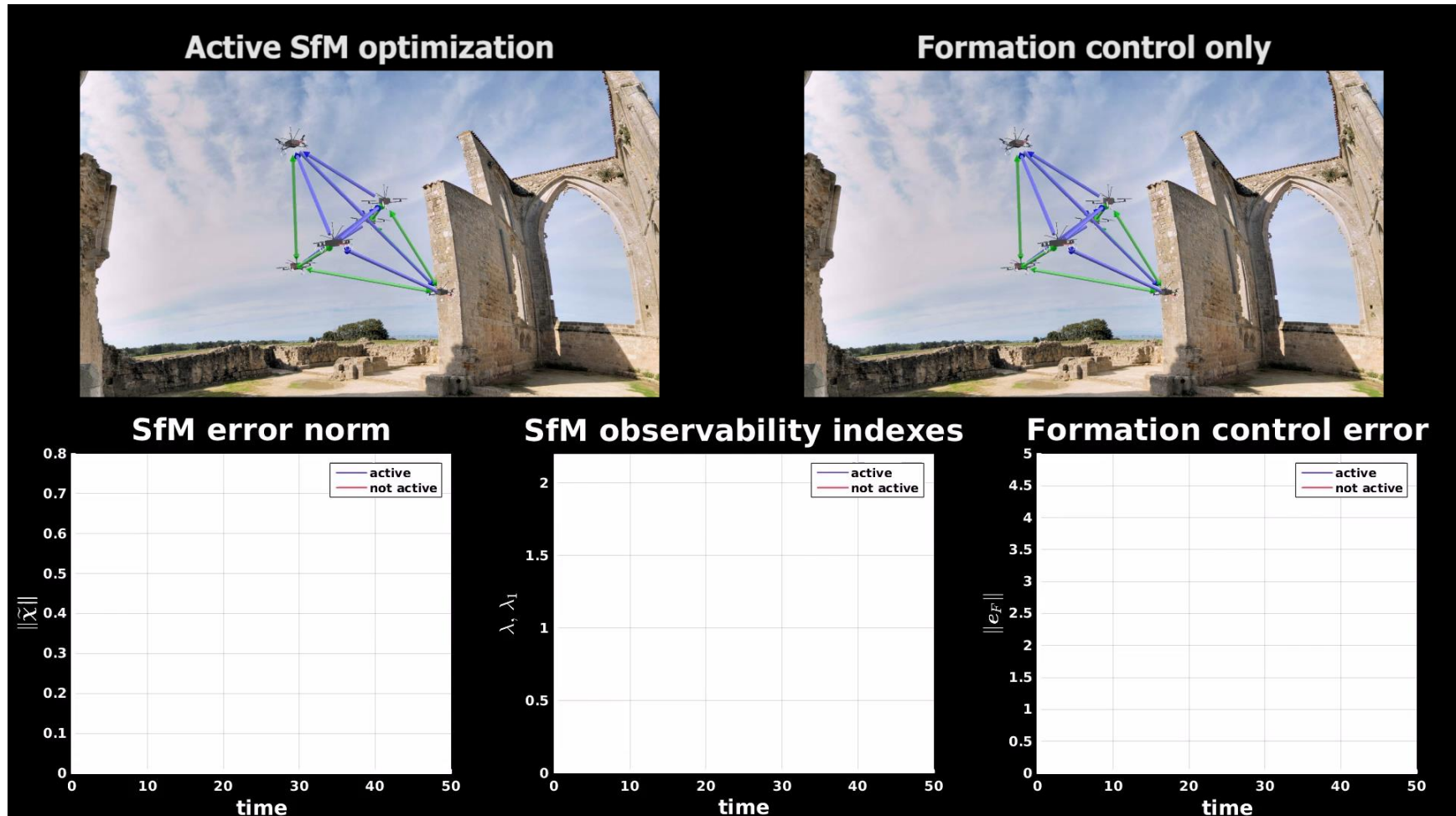
$$\dot{w}_{\bar{\lambda}} \propto k_{\bar{\lambda}}(E) \frac{\partial \bar{\lambda}}{\partial w_{\bar{\lambda}}}^T$$



- consensus on $\bar{\mathbf{p}}, \bar{\lambda}, E, \frac{\partial \bar{\lambda}}{\partial w_{\bar{\lambda}}}, w_{\bar{\lambda}}$



Simulations of bearing-constrained active estimation



R. Spica, and P. Robuffo Giordano, "Active Decentralized Scale Estimation for Bearing-Based Localization," In IEEE/RSJ IROS 2016, Daejeon, Korea, October 2016.

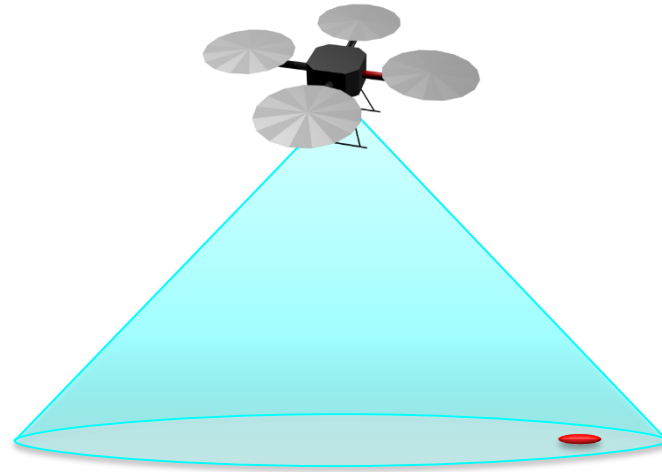
Wrapping up

- we obtained
 - correctly **scaled decentralized localization** of the agents
 - **decentralized maximization** of distance estimation performance
 - active perception **coupled with** bearing **formation control**
- open points
 - localization performance also depends of formation **rigidity**
$$\{\lambda_{ij}\} \cup \text{eigs}(\mathcal{B}_{\mathcal{G}}^A(\mathbf{q})\mathcal{B}_{\mathcal{G}}^A(\mathbf{q})^T)$$
 - estimating a **single metric scale** (not multiple distances) would guarantee consistence with the bearing measurements
 - **trajectory planning** could improve performance (non myopic)

Vision-Based Model Predictive Control of Quadrotor UAVs

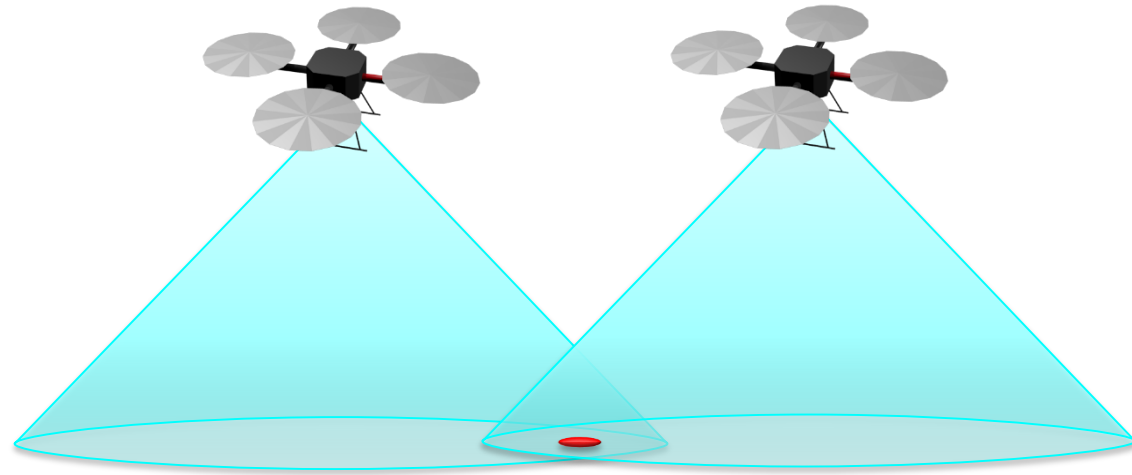
Bryan Penin, Riccardo Spica, Paolo Robuffo Giordano
and Francois Chaumette

Context



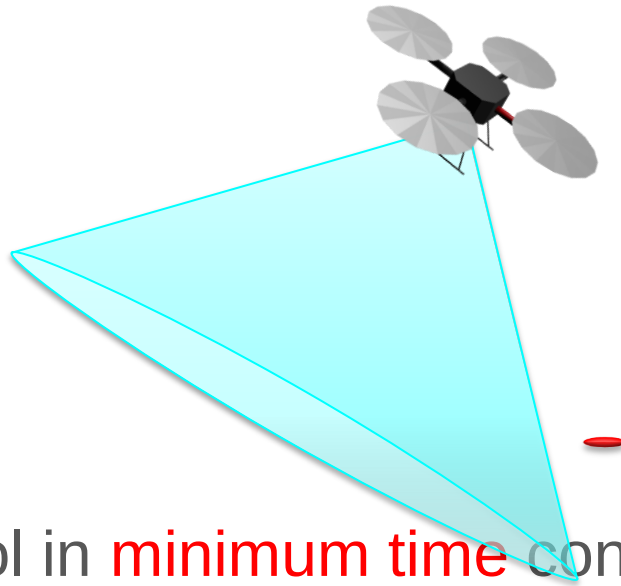
- visual control in **minimum time** considering
 - quadrotor **dynamics** (under-actuation)
 - limited **actuation** (force/torque) and **field of view** (possibly relaxed)
- partially known state (e.g. target dimension)
 - structure from motion to estimate the state
 - **observability** is an additional objective/constraint
 - online reactive re-planning (MPC)

Context



- visual control in **minimum time** considering
 - quadrotor **dynamics** (under-actuation)
 - limited **actuation** (force/torque) and **field of view** (possibly relaxed)
- partially known state (e.g. target dimension)
 - structure from motion to estimate the state
 - **observability** is an additional objective/constraint
 - online reactive re-planning (MPC)

Context



- visual control in **minimum time** considering
 - quadrotor **dynamics** (under-actuation)
 - limited **actuation** (force/torque) and **field of view** (possibly relaxed)
- partially known state (e.g. target dimension)
 - structure from motion to estimate the state
 - **observability** is an additional objective/constraint
 - online reactive re-planning (MPC)

Optimization problem

- **objective**
- **constraints**
 - **current** robot **state**
(from vision + IMU)
 - targets in the camera
limited field of view
 - **desired** robot **state**
 - quadrotor full
nonlinear **dynamics**
 - **limited** control **inputs**
(propeller speed)

$$\min_{\mathbf{u}(s), T} T$$
$$s.t.$$

$$\chi(t) = \chi_t$$

$$\beta_i(s) \in \Omega, \forall s \in [t, t + T]$$

$$\chi(t + T) = \chi^*$$

$$\dot{\chi} = h(\chi, u)$$

$$u(s) \in \mathcal{U}, \forall s \in [t, t + T]$$

Optimization problem

- **objective**
- **constraints**
 - **current** robot **state**
(from vision + IMU)
 - targets in the camera
limited field of view
 - **desired** robot **state**
 - quadrotor full
nonlinear **dynamics**
 - **limited** control **inputs**
(propeller speed)

$$\min_{u(s)} \int_t^T$$

$s.t.$ infinite dimensional search space

$$\chi(t) = \chi_t$$

$$\beta_i(s) \in \Omega, \forall s \in [t, t + T]$$

$$\chi(t + T) = \chi^*$$

$$\dot{\chi} = h(\chi, u)$$

nonlinear differential equality constraints

$$u(s) \in \mathcal{U}, \forall s \in [t, t + T]$$

- no analytic solution → **numerical optimization**

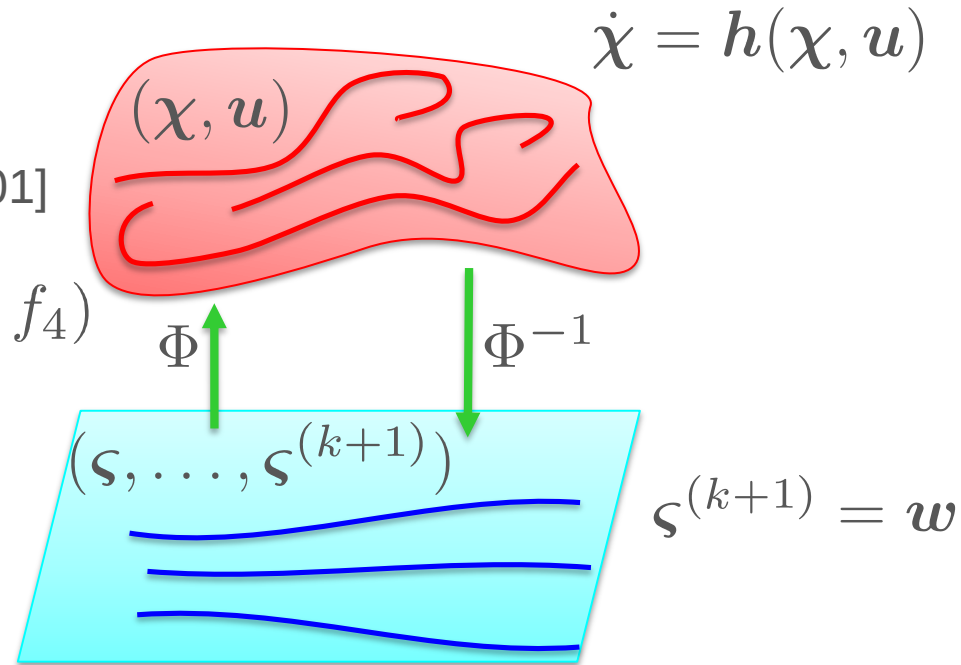
Numerical formulation

- differential **flatness**

- for quadrotors [Mistler et al. 2001]

$$\chi = (p, v, R, \omega), \quad u = (f_1, f_2, f_3, f_4)$$

$$\varsigma = (p, \psi), \quad w = (p^{(4)}, \ddot{\psi})$$



- trajectory **parametrization**

$$\varsigma(s) = \sum_{j=1}^n B_{j,d} \left(\frac{s-t}{T} \right) p_j, \quad \forall s \in [t, t+T]$$

B-spline basis functions
sufficiently smooth to
guarantee continuity of χ

limited number of
control points to be
numerically optimized

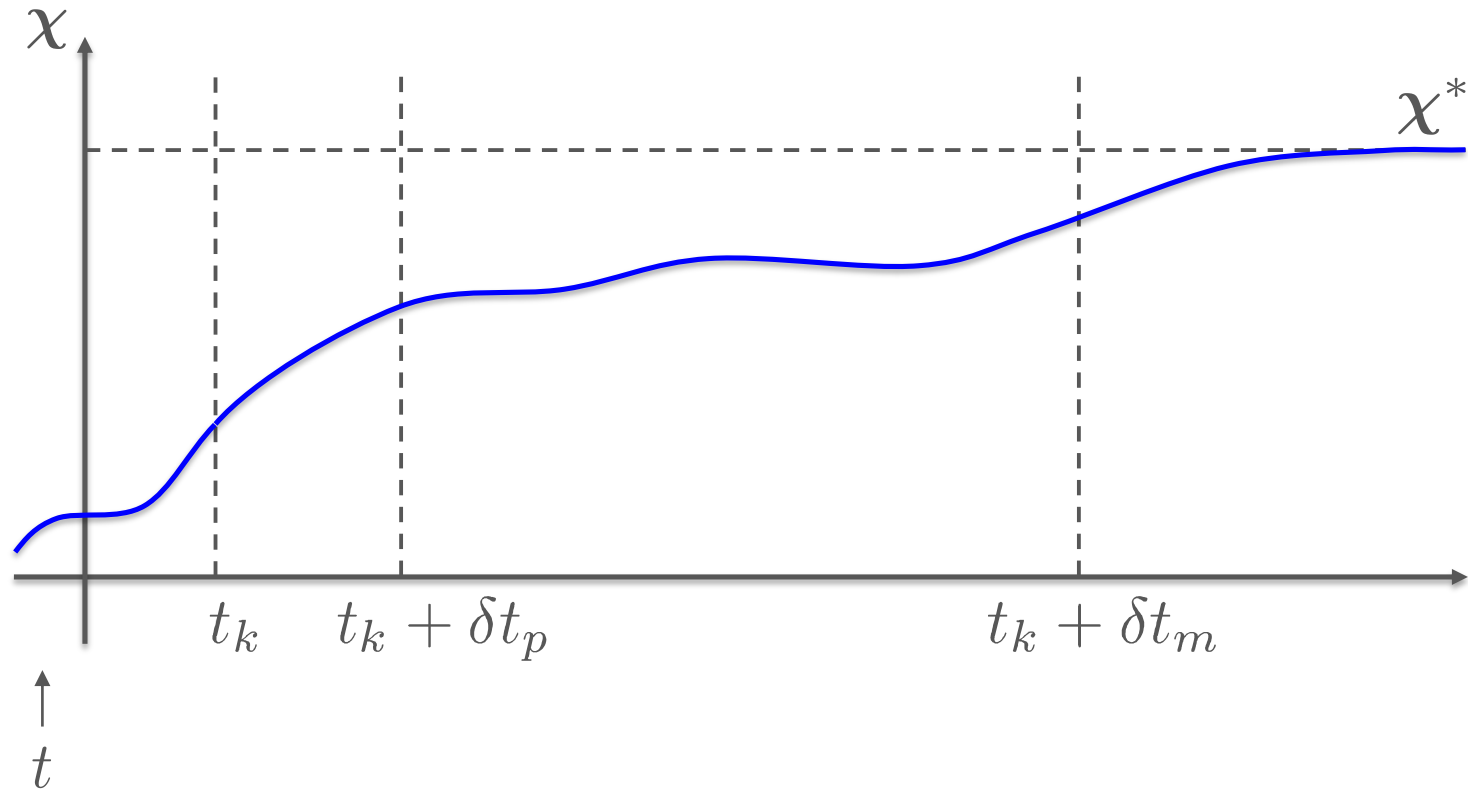
Overall architecture

- optimization problem ($\sigma_{\chi} = (p, \dot{p}, \ddot{p}, \ddot{p}, \psi, \dot{\psi})$)

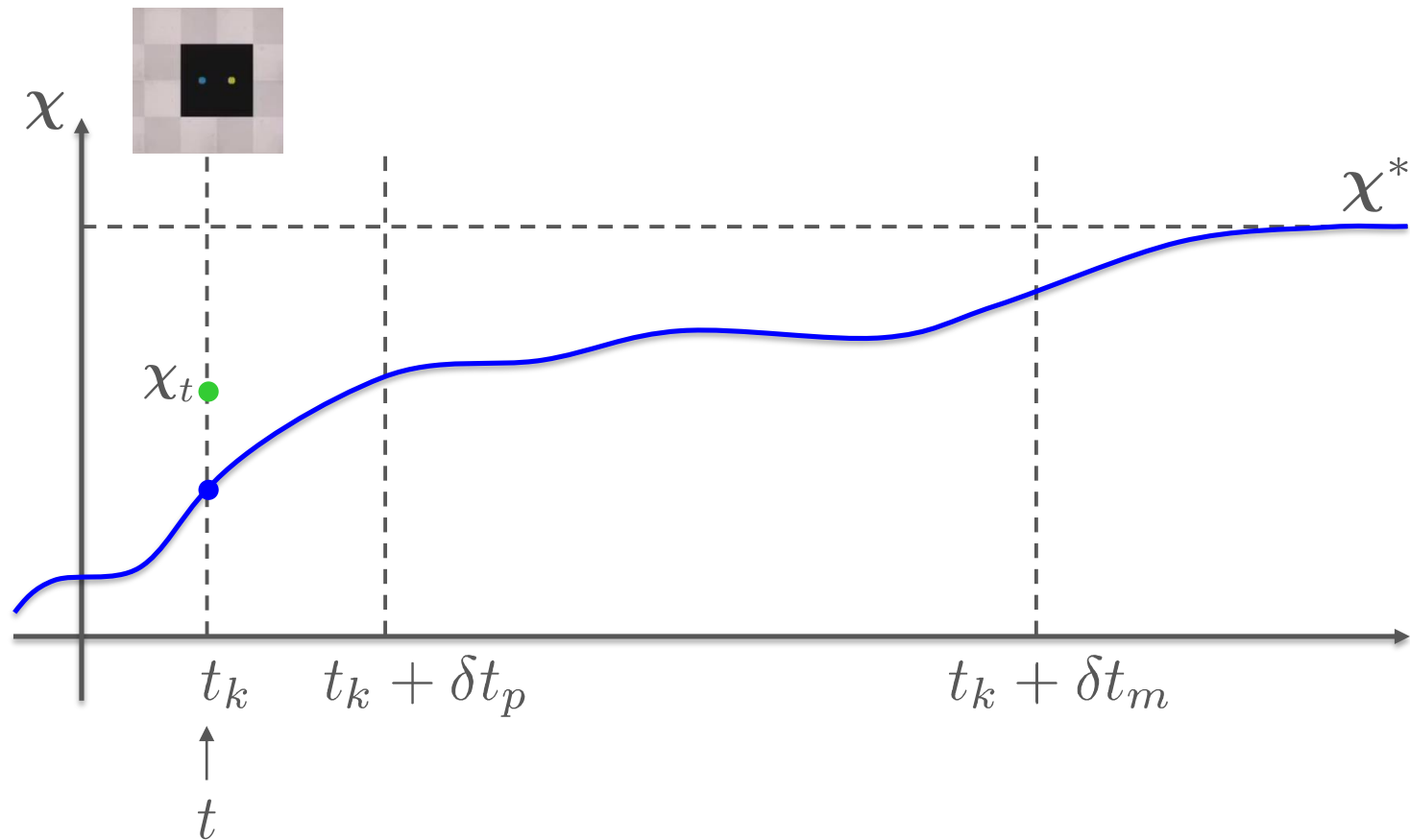
$$\begin{aligned} \min_{p_1, \dots, p_n, T} \quad & T \\ \text{s.t.} \quad & \sigma_{\chi}(t) = \sigma_t = \phi_{\chi}^{-1}(\chi_t), \\ & \sigma_{\chi}(t+T) = \sigma^* = \phi_{\chi}^{-1}(\chi^*), \\ & \beta_i(s) \in \Omega, \forall s \in [t, t+T], i = 1, \dots, N, \\ & u(s) \in \mathcal{U}, \forall s \in [t, t+T], \end{aligned}$$

- numerical **resolution** takes $\delta t_p = 40$ ms
- visual **measurements** ($\rightarrow \chi_t$) available every $\delta t_m = 80$ ms
- IMU **odometry** and a **nonlinear trajectory tracker** [Lee et al. 2010] to track the generated optimal trajectories
- online **re-planning** to cope with uncertainties

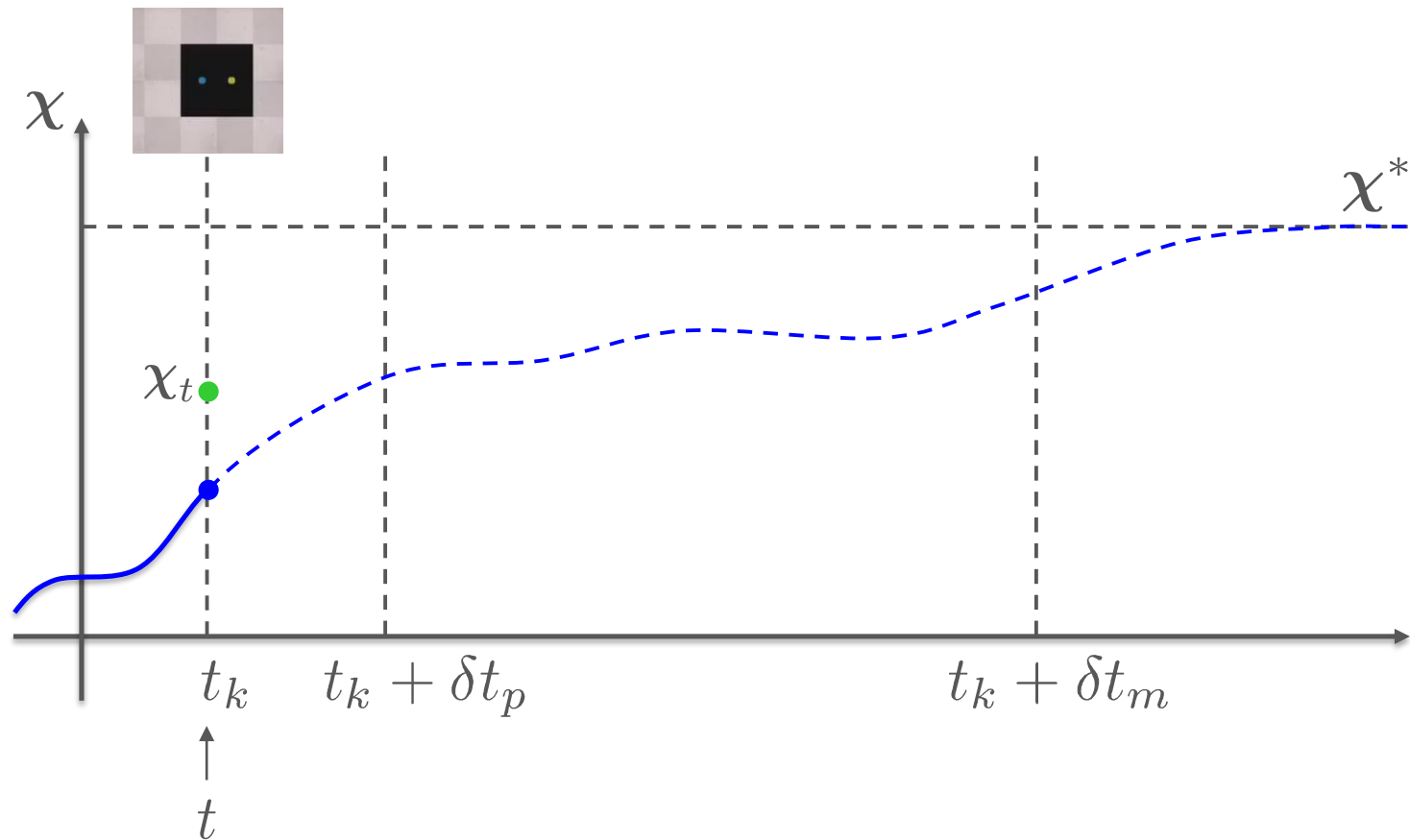
Online re-planning



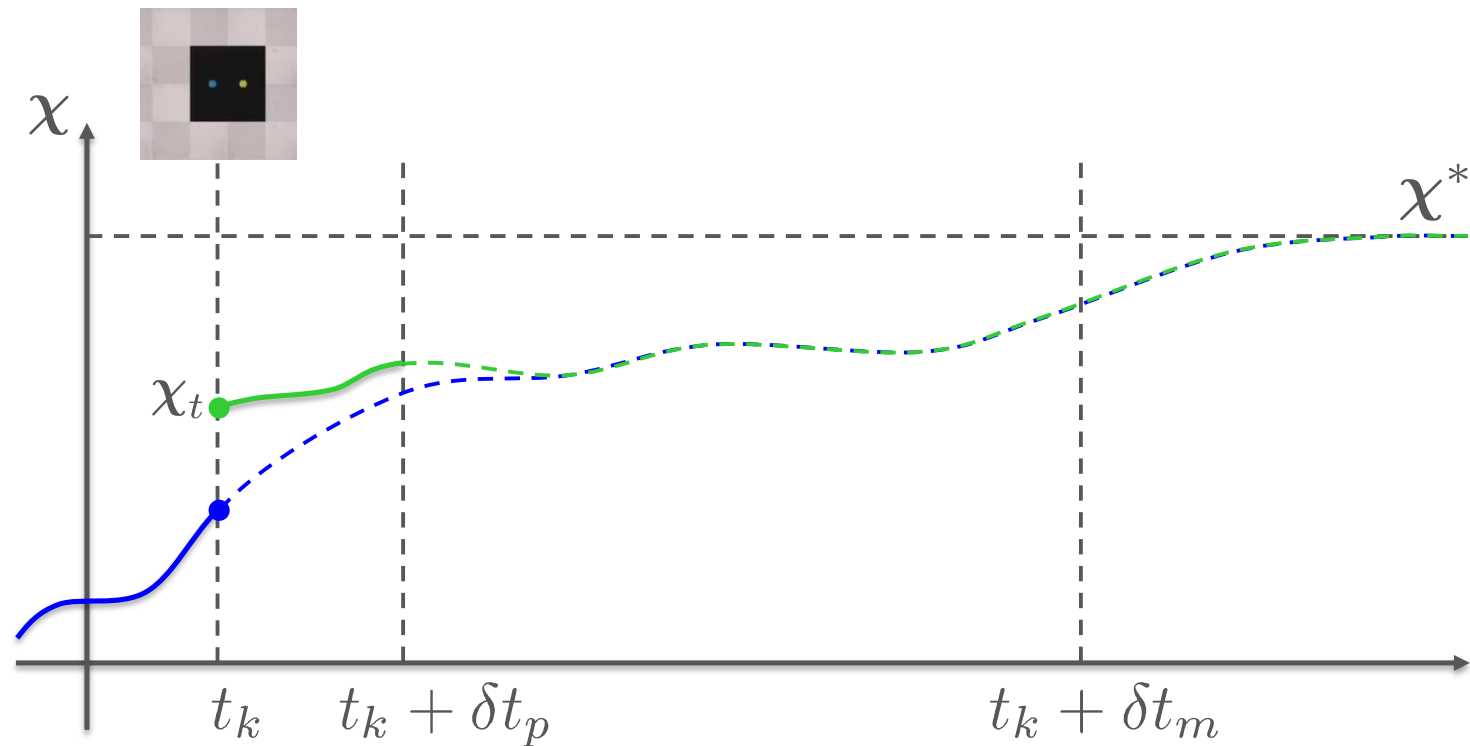
Online re-planning



Online re-planning



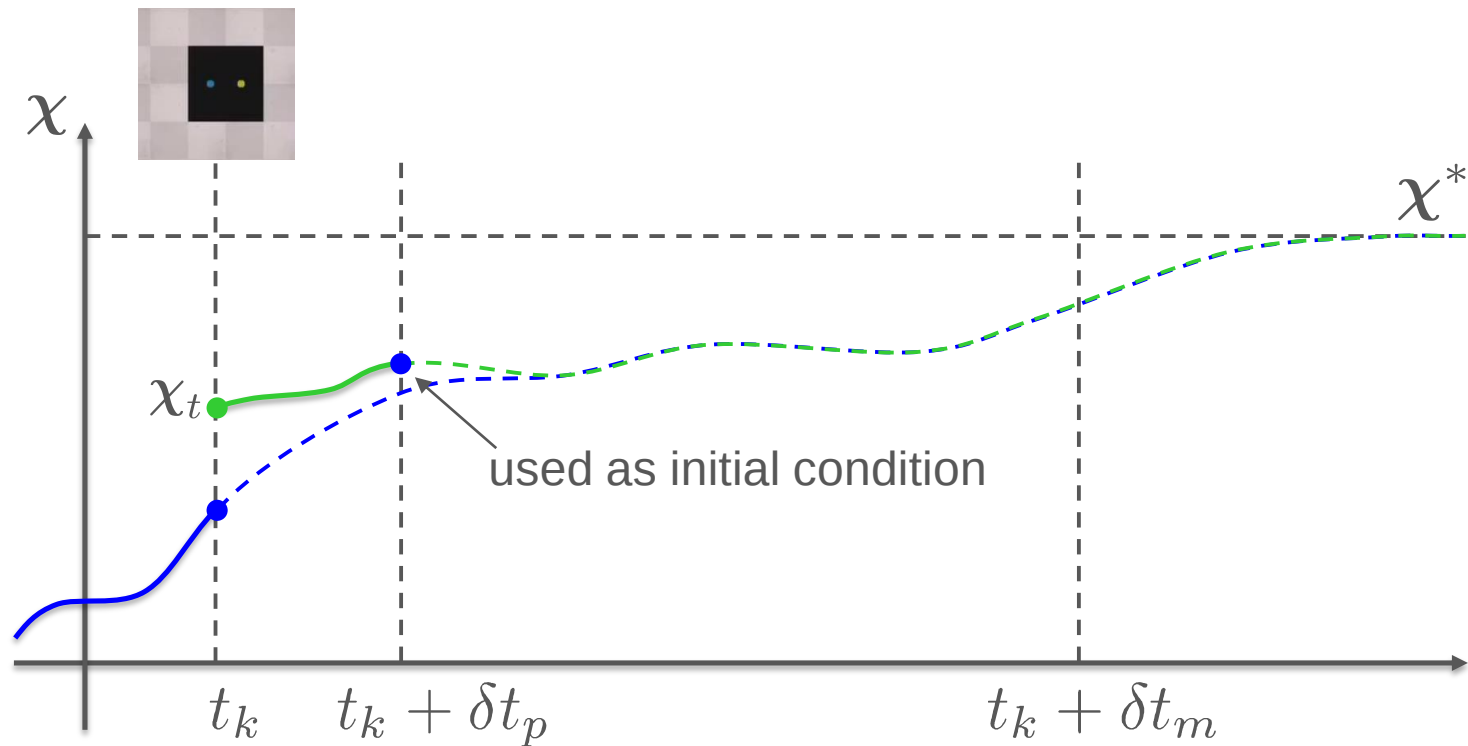
Online re-planning



$$\min_{\mathbf{p}_1^-, \dots, \mathbf{p}_n^-} \quad \frac{1}{2} \sum_{j=1}^n \|\mathbf{p}_j - \mathbf{p}_j^-\|^2$$

$$s.t. \quad \chi(t) = \chi_t$$

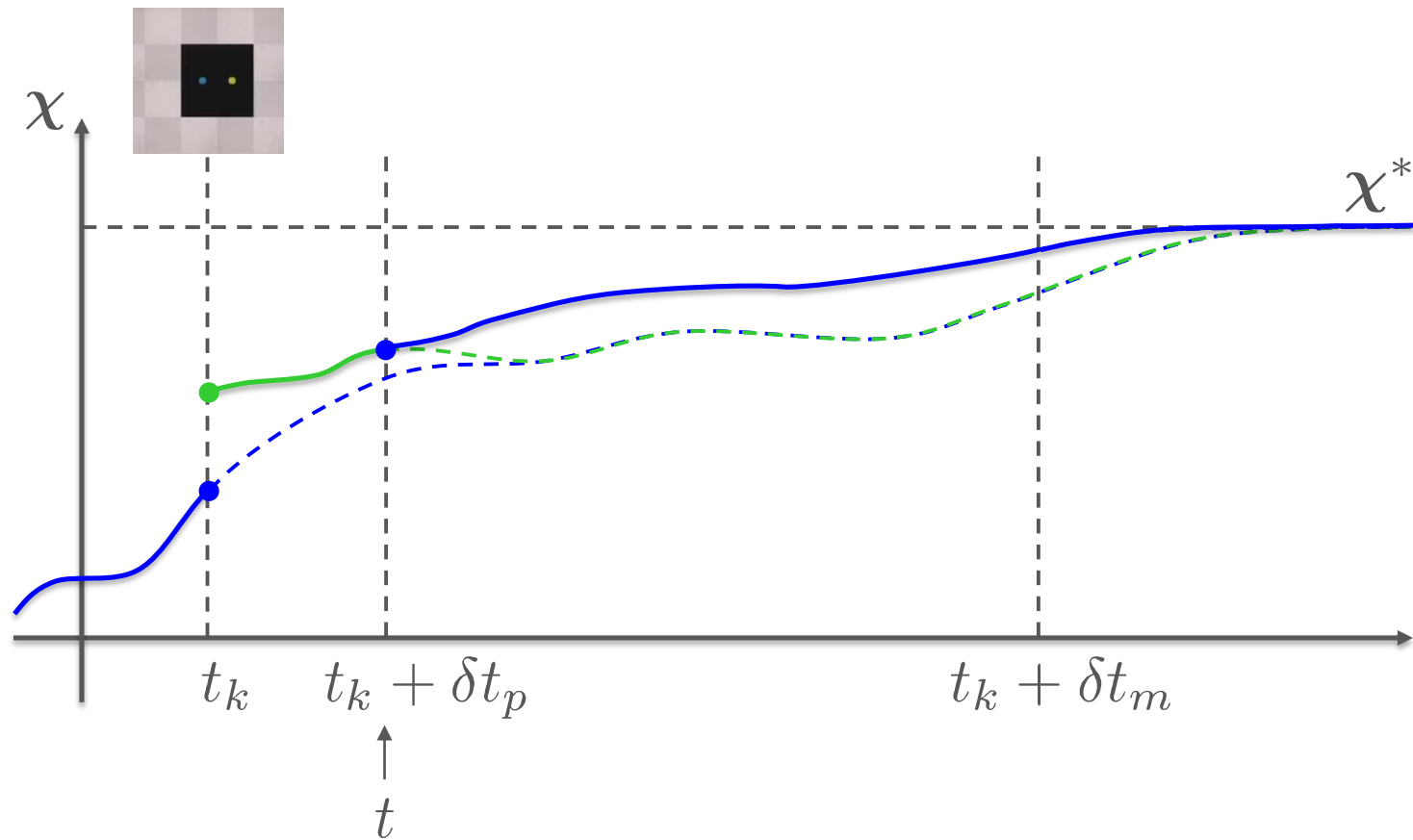
Online re-planning



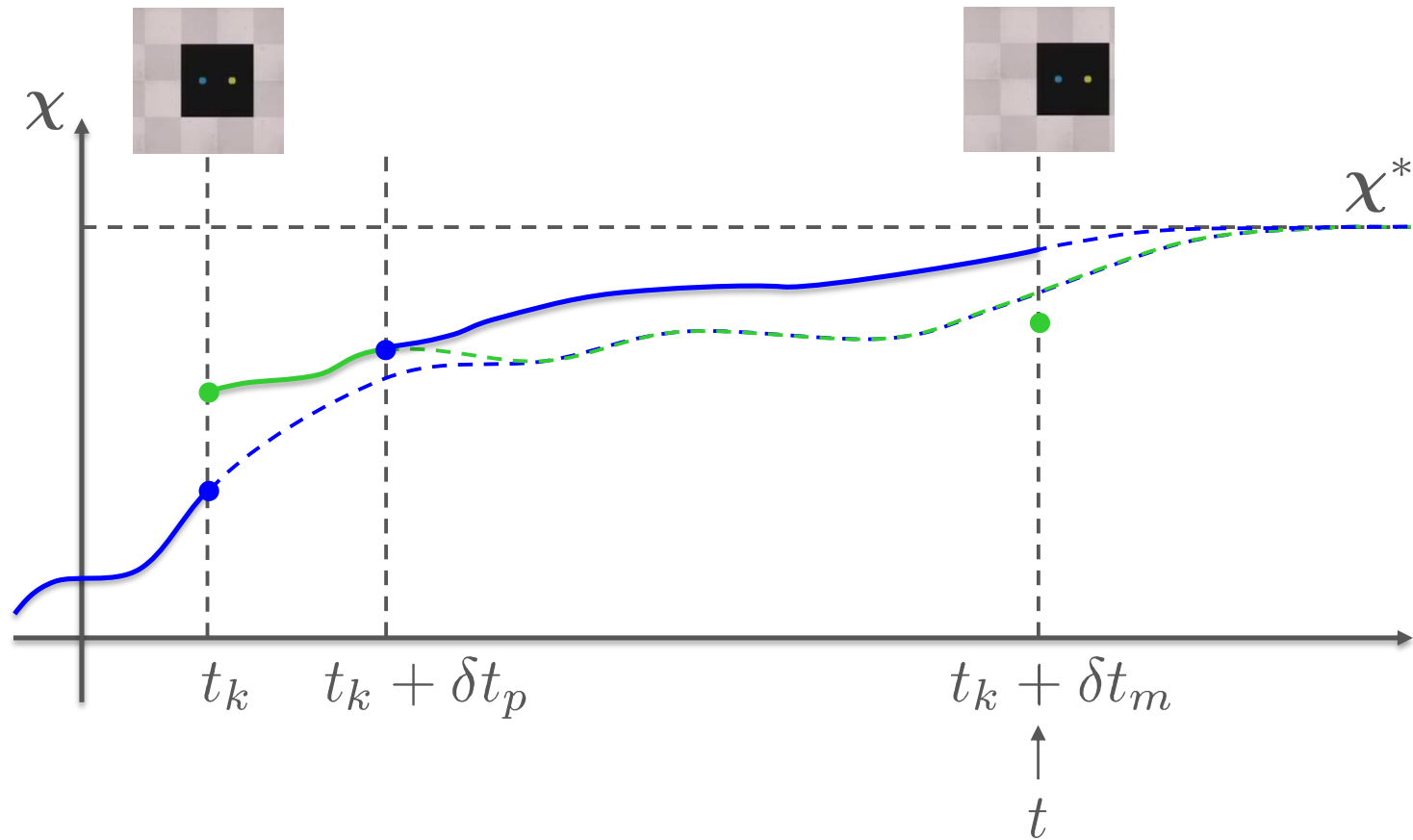
$$\min_{\mathbf{p}_1^-, \dots, \mathbf{p}_n^-} \quad \frac{1}{2} \sum_{j=1}^n \|\mathbf{p}_j - \mathbf{p}_j^-\|^2$$

$$s.t. \quad \chi(t) = \chi_t$$

Online re-planning



Online re-planning



Simulation results

Vision-Based Minimum-Time Trajectory Generation for a Quadrotor UAV

Bryan Penin, Riccardo Spica, Paolo Robuffo Giordano, François Chaumette



B. Penin, R. Spica, P. Robuffo Giordano, and F. Chaumette, "Vision-Based Minimum-Time Trajectory Generation and Control of a Quadrotor UAV," In IEEE ICRA 2017, Singapore, May 2017, **under review**.

Conclusions

- we generate minimum time trajectories considering
 - full **underactuated dynamics** (no near-hovering)
 - system **limitations** in terms of
 - propeller thrust
 - camera field of view
- future work
 - **speed up** optimization with C++ implementation (NLOPT)
 - real **experiments**
 - **relax** visibility **constraints** introducing “blind” phases
 - introduce additional constraints (e.g. **active estimation**)

Thank you for your attention

Riccardo Spica

Lagadic group

Inria Rennes Bretagne Atlantique & IRISA

<http://www.irisa.fr/lagadic>