Cooperative Multi-robot Systems: From Perception to Action

Fabio Morbidi

Laboratoire MIS
Université de Picardie Jules Verne

Soutenance HDR

Parrain HDR : Prof. E. Mouaddib

31 janvier 2024

Outline

- **Part I**
  - Academic background
  - Research projects
  - Professional and teaching activities
- **Part II**
  - Multi-robot systems: generalities
  - Formation control of mobile robots
  - Coordinated control of multi-robot systems
  - Conclusion and future research
  - Acknowledgements

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- **2009**: PhD in Robotics and Automation
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- **2014-present**: Maître de Conférences, section CNU 61
  Laboratoire MIS, Université de Picardie Jules Verne

Supervision of PhD students

- **Defended**
  - J. Caracotte (July 2021), post-doc at UPJV
  - G. Hardouin (March 2022), project manager at Naval Group
  - D. Adlakha (December 2022), post-doc at Univ. Clermont-Auvergne

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- **Ongoing**
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  - D. Rossi (2nd year)
  - A. El Moudni (2nd year)

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    - D. Rodrigues da Costa (3rd year)
    - D. Rossi (2nd year)
    - A. El Moudni (2nd year)
- **Upcoming**
    - 2 PhD students to start in October 2024

Research projects

- **EVELOC** (ANR-FWF, France-Austria, 2024-2028)
- **DEVIN** (ANR TSIA, 2024-2028)
- **CERBERE** (ANR PRCE, 2021-2025)
  - PhD of D. Rossi (with P. Vasseur) and A. El Moudni (with R. Boutteau)
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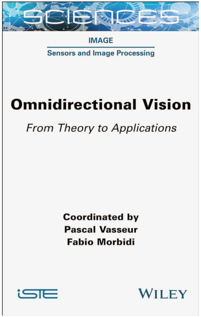
  - PhD of G. Hardouin (with E. Mouaddib)
- **ADAPT** (Interreg VA, France (Channel) England, 2017-2022)
  - Post-doc: H.E. Benseddik (2018-2019)
  - Research engineer: S. Delmas (2019-2021)

Publications

	Total	**w/ students**
Book	1	
Int. journal	24	**5**
Book chapter	4	
Int. conference	42	**7**
Nat. journal	2	
Nat. conference	2	



SCIENCES

IMAGE

Sensors and Image Processing

Omnidirectional Vision

From Theory to Applications

Coordinated by
Pascal Vasseur
Fabio Morbidi

iSTE WILEY

December 2023

Professional activity and responsibilities

- Associate Editor
    - **Journals**
        - IEEE Transactions on Robotics (2022-present)
        - IEEE Robotics and Automation Letters (2022-present)
    - **Conferences**
        - IEEE ICRA 2017-2024
        - IEEE/RSJ IROS 2020-2022 and 2024

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- Head of the Robotic Perception group (2022-present)
  - 9 + 1 permanents
  - 7 PhD students

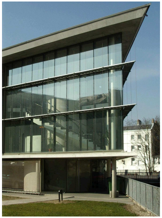
Teaching

Master courses related to my research:

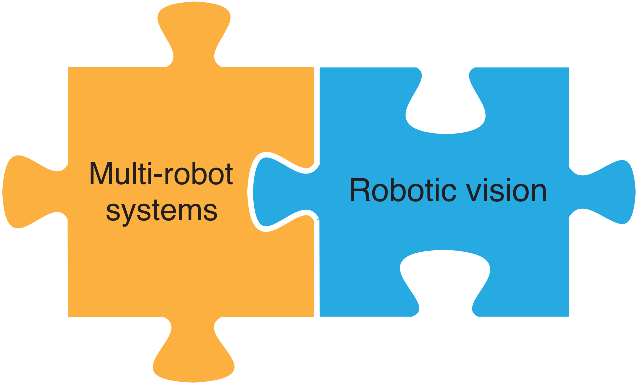
- *Systèmes Robotiques Hétérogènes et Coopératifs* (2018-present)
- *Surveillance Distribuée de Systèmes Multi-Agents* (2018-2023)
- *Perception Avancée et Robotique Mobile* (2016-present)
- *Localisation et Navigation de Robots* (2016-present)

Département EEA

Electronique
Energie Electrique
Automatique



Research interests



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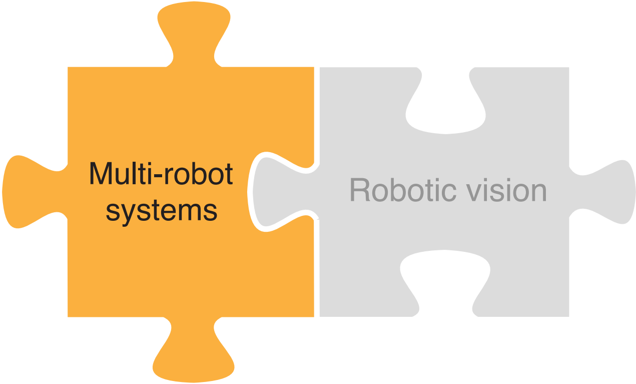


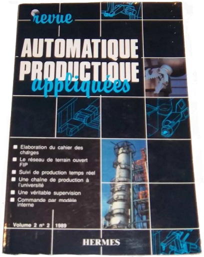
Multi-robot systems

Robotic vision

Multi-robot systems: an old tradition . . .

- **Robotic Perception group**
  - Pioneer, back to 1990!

“*Hiérarchie et communication pour une équipe de robots mobiles. Synchronisation des actions*”, C. Pégard, J. Arnould, A. Lebrun, E. Mouaddib, B. Dolphin, Revue d’Automatique et de Productique Appliquées, (3)2, 83-102, 1990



revue
AUTOMATIQUE
PRODUCTIQUE
appliquées

- Elaboration du cahier des charges
- Le réseau de terrain ouvert FIP
- Suivi de production temps réel
- Une chaîne de production à l'université
- Une véritable supervision
- Commande par modèle interne

Volume 2 n° 2 1989

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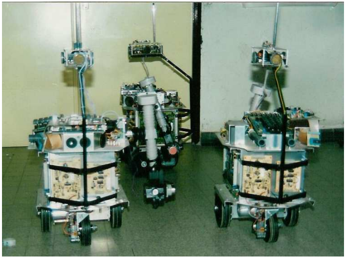

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Multi-robot systems: generalities

Nature

Multi-robot systems: generalities

Nature

Technology

Multi-robot systems: generalities

Nature

Technology

Definition A multi-robot system is a set of n autonomous robots working together to achieve a *common task*

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Formation control

Goal Find the control inputs of n mobile robots in order to generate a predefined **pattern** (fixed or time-varying)

Formation control

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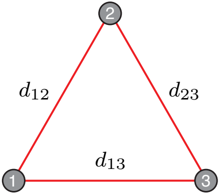
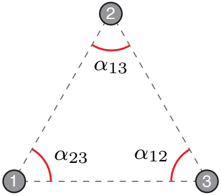
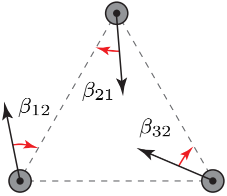
- Criteria to define the pattern [Oh *et al.*, 2015], [Ahn, 2020]:
  - Absolute poses $\mathbf{q}_i$
  - Relative distances d_{ij}
  - Relative orientations α_{ij}
  - Bearing angles β_{ij}
  - A combination of distances and angles



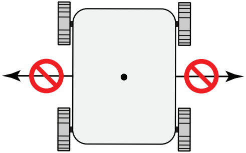


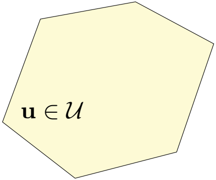


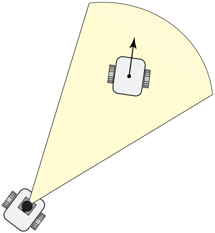
Formation control: challenges

Q1: How to handle additional constraints?

- Kinodynamic constraints
- Input constraints ($\mathbf{u} \in \mathcal{U}$)
- Connectivity/visibility constraints
- Stability







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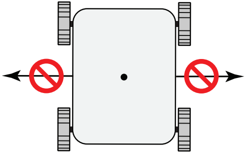
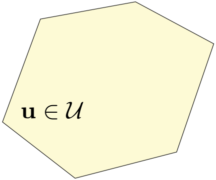
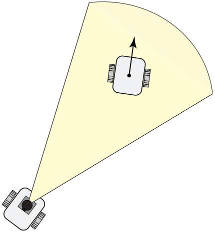


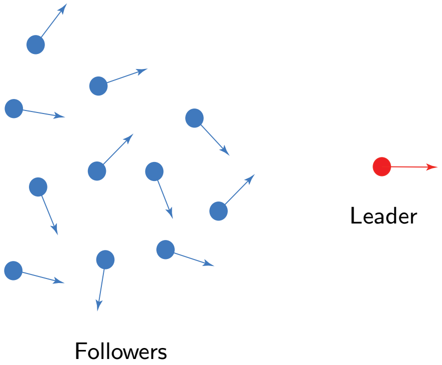




Q2: What is their impact on formation achievement?

Leader-follower formations

- Two classes of robots: **leader** and **followers**
- The leader moves along a given trajectory
- The followers have to pursue the leader



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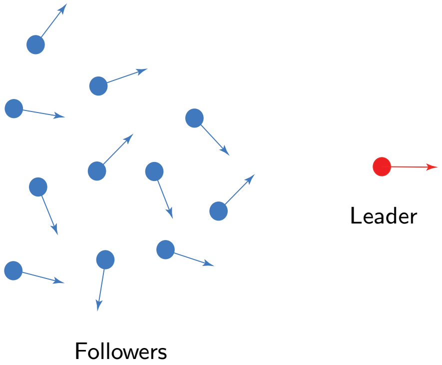
Video (GRASP lab)



Unicycle robot

Kinematic model:

$$\begin{cases} \dot{x} = v\cos\theta \\ \dot{y} = v\sin\theta \\ \dot{\theta} = \omega \end{cases}$$

- $\mathbf{q} = [x,\, y,\, \theta]^T \in \mathbb{R}^2 \times \mathbb{S}^1$: pose of the robot
- $\mathbf{u} = [v,\, \omega]^T$: control input

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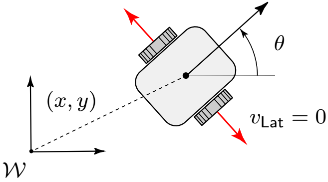
Nonholonomic constraint: $v_{\text{Lat}} = 0$



During my PhD and post-doc

- **Input constraints** $(v, \omega) \in \mathcal{U}$ [Consolini *et al.*, 2008]:
    - How does $\mathcal{U}$ affect the *achievement* of a desired formation?
    - Design a stabilizing controller that explicitly accounts for $\mathcal{U}$

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  - Robots only equipped with *panoramic cameras*
  - *Nonlinear observability analysis* to identify the most favorable trajectories of the leader to maintain a desired formation

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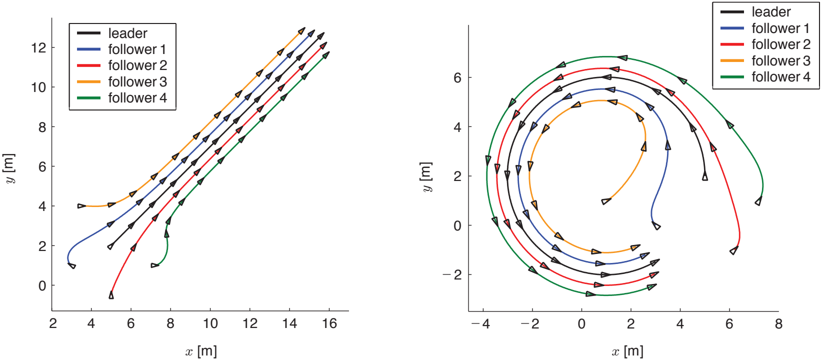
  - Robots only equipped with *panoramic cameras*
  - *Nonlinear observability analysis* to identify the most favorable trajectories of the leader to maintain a desired formation
- **Human-robot formation control** via visuo-haptic feedback [Scheggi *et al.*, 2014]

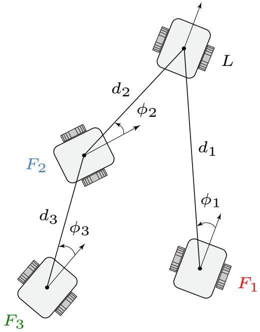
During my PhD and post-doc

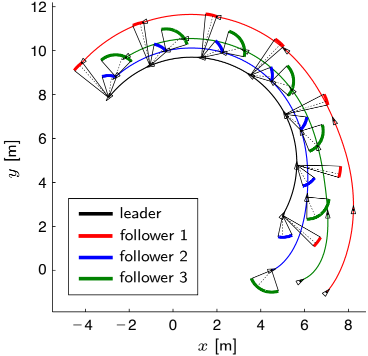
- Wedge formation with 4 followers [Consolini *et al.*, 2008]
    - Distance-bearing constraints: $(d_i,\ \phi_i)$, $i \in \{1, 2, 3, 4\}$



During my PhD and post-doc

- Hierarchical formation with 3 followers [Consolini *et al.*, 2009]
  - Distance-bearing constraints: $(d_i,\ \phi_i)$, $i \in \{1, 2, 3\}$

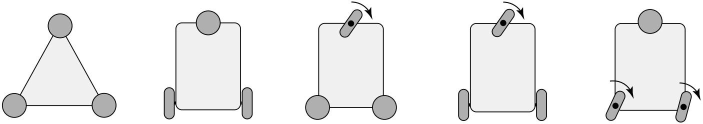




Mobility of formations of unicycles

Classification of a wheeled robot by **type** [Campion *et al.*, 1996]:

- δ_m: degree of mobility
- δ_s: degree of steerability



Omnidirectional $(3,\ 0)$

Unicycle $(2,\ 0)$

Omni-steer $(2,\ 1)$

Tricycle $(1,\ 1)$

Two-steer $(1,\ 2)$

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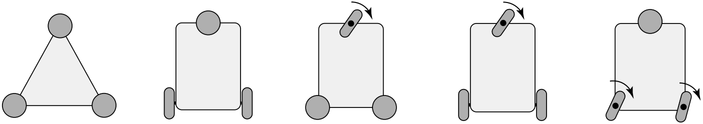

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Problem Is it possible to extend the classification by type $(\delta_m,\ \delta_s)$ to *distance-bearing formations* of unicycles?

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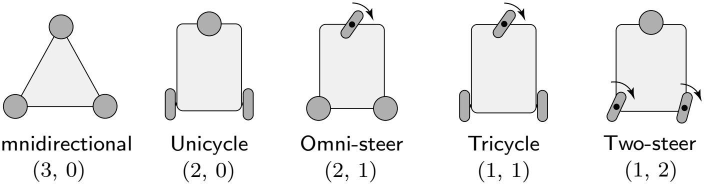


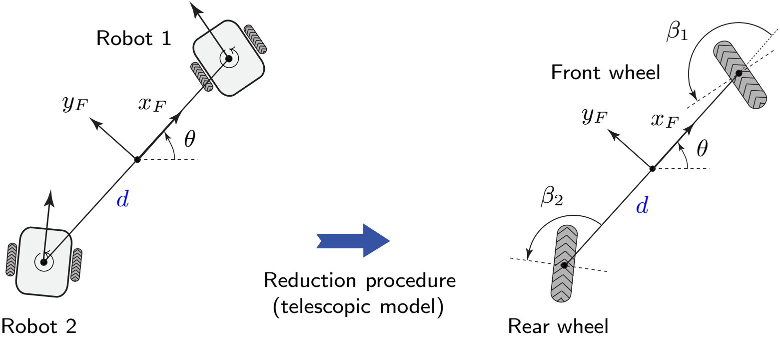
Problem Is it possible to extend the classification by type $(\delta_m,\ \delta_s)$ to *distance-bearing formations* of unicycles?

Simplifying assumptions:

- Centered fixed or steering wheels only
- Robots disposed at the vertices of regular convex polygons

Mobility of formations of unicycles

Idea Notion of **macro-robot** [Morbidi & Bretagne, 2018]



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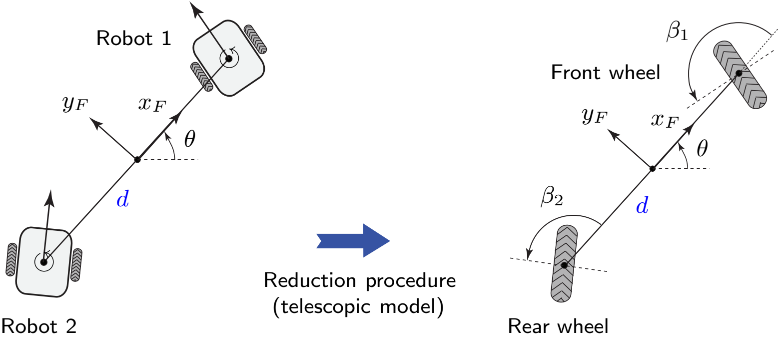

Reduction procedure
(telescopic model)

- Parallels with concepts in the single-robot case (synchro-drive robot, singular wheels configuration, etc.)

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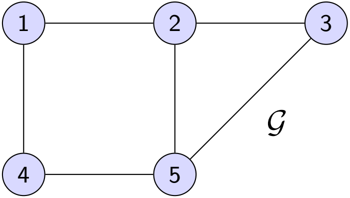
Graph theory

Undirected graph $\mathcal{G} = (V,\, E)$:



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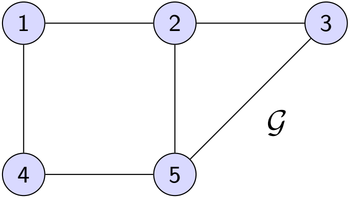

Degree matrix

$$\mathbf{D} = \begin{bmatrix} 2 & 0 & 0 & 0 & 0 \\ 0 & 3 & 0 & 0 & 0 \\ 0 & 0 & 2 & 0 & 0 \\ 0 & 0 & 0 & 2 & 0 \\ 0 & 0 & 0 & 0 & 3 \end{bmatrix}$$

Adjacency matrix

$$\mathbf{A} = \begin{bmatrix} 0 & 1 & 0 & 1 & 0 \\ 1 & 0 & 1 & 0 & 1 \\ 0 & 1 & 0 & 0 & 1 \\ 1 & 0 & 0 & 0 & 1 \\ 0 & 1 & 1 & 1 & 0 \end{bmatrix}$$

Laplacian matrix

$$\mathbf{L} = \begin{bmatrix} 2 & -1 & 0 & -1 & 0 \\ -1 & 3 & -1 & 0 & -1 \\ 0 & -1 & 2 & 0 & -1 \\ -1 & 0 & 0 & 2 & -1 \\ 0 & -1 & -1 & -1 & 3 \end{bmatrix}$$

Consensus protocol

- n single integrators: $\dot{x}_i(t) = u_i(t)$
- Control input:

$$u_i(t) = \sum_{j \in \mathcal{N}(i)} (x_j(t) - x_i(t)), \; i \in \{1, \ldots, n\}$$

- Collective dynamics [Olfati-Saber *et al.*, 2007]:

$$\boxed{\dot{\mathbf{x}}(t) = -\mathbf{L}\,\mathbf{x}(t)}$$

with $\mathbf{x} = [x_1, \ldots, x_n]^T$

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Building block to design distributed algorithms :

- Formation control
- Cooperative environmental monitoring
- Cooperative active target tracking
- Cooperative 3D reconstruction

Consensus protocol

- n single integrators: $\dot{x}_i(t) = u_i(t)$
- Control input:

$$u_i(t) = \sum_{j \in \mathcal{N}(i)} (x_j(t) - x_i(t)), \;\; i \in \{1, \ldots, n\}$$

- Collective dynamics [Olfati-Saber *et al.*, 2007]:

$$\boxed{\dot{\mathbf{x}}(t) = -\mathbf{L}\,\mathbf{x}(t)}$$

with $\mathbf{x} = [x_1, \ldots, x_n]^T$

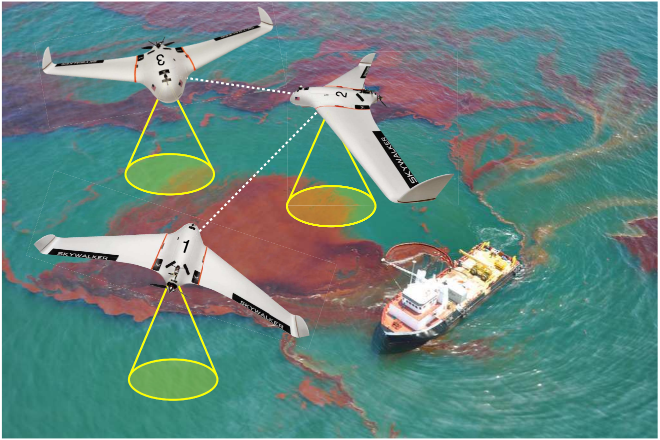
Building block to design distributed algorithms :

- Formation control

$$\left.\begin{array}{l}\text{• Cooperative environmental monitoring}\\ \text{• Cooperative active target tracking}\\ \text{• Cooperative 3D reconstruction}\end{array}\right\} \textbf{UAVs}$$

Cooperative environmental monitoring

Goal Monitor a 2D environment with a swarm of fixed-wing UAVs



Cooperative environmental monitoring

In [Morbidi *et al.*, 2011]:

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$$\boxed{\text{Moments of the swarm}} \longleftrightarrow \textbf{MATCH} \longleftrightarrow \boxed{\text{Moments of the particles}}$$

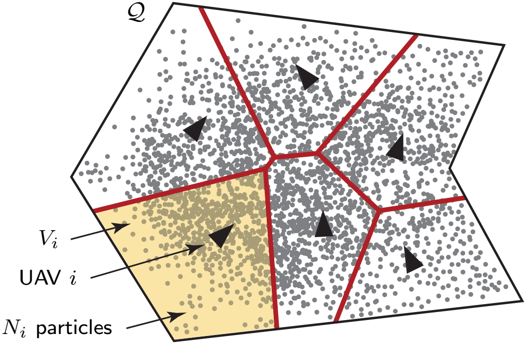
$$\mathbf{f}(\mathbf{q}) = \frac{1}{n}\sum_{i=1}^{n} \boldsymbol{\phi}(\mathbf{q}_i) \qquad \mathbf{f}^{\star}_{\text{env}} = \frac{1}{N}\sum_{k=1}^{N} \boldsymbol{\phi}(\mathbf{q}_k)$$

$$\boldsymbol{\phi}(\mathbf{q}_i) = [q_{ix}, q_{iy}, q_{ix}^2, q_{iy}^2, q_{ix}q_{iy}, q_{ix}^3, q_{iy}^3, q_{ix}^2 q_{iy}, \ldots]^T$$

Moment-generating function

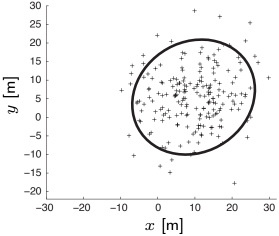
Cooperative environmental monitoring

- Each UAV processes only the particles inside the Voronoi cell V_i of the environment $\mathcal{Q}$ that it generates
- Each UAV locally estimates $\mathbf{f}(\mathbf{q})$ and $\mathbf{f}^{\star}_{\text{env}}$ by running a **PI average consensus estimator** [Lynch *et al.*, 2008]

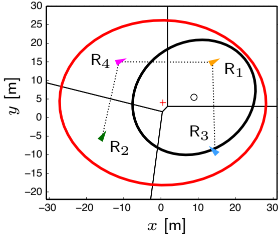


Cooperative environmental monitoring

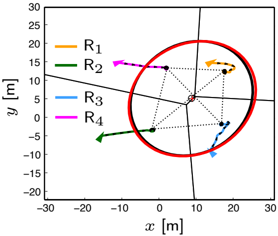
- **Simulation**



$N = 200$ particles and ellipse of desired geometric moments of the swarm (**black**)



Initial pose of the UAVs and ellipse of geometric moments (**red**)



Trajectory of the UAVs and final ellipses of geometric moments

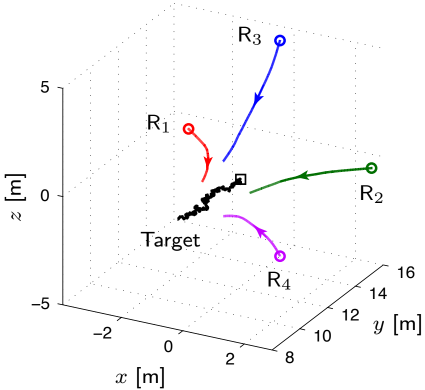
- **Animation**

Cooperative active target tracking

- A moving target and n cooperating mobile robots

Cooperative active target tracking

Goal Control the n robots along paths that **minimize** the **combined uncertainty** about the target's position



Cooperative active target tracking

n **double-integrator** aerial vehicles [Morbidi & Mariottini, 2013]:

$$\begin{aligned} \dot{\mathbf{p}}_i &= \mathbf{q}_i, \\ \dot{\mathbf{q}}_i &= \mathbf{u}_i, \quad i \in \{1, \ldots, n\} \end{aligned}$$

- $\mathbf{p}_i \in \mathbb{R}^3$: position of robot i
- $\mathbf{q}_i \in \mathbb{R}^3$: velocity of robot i
- $\mathbf{u}_i \in \mathbb{R}^3$: control input of robot i

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- $\mathbf{u}_i \in \mathbb{R}^3$: control input of robot i

Assumptions:

- The position $\mathbf{p}_i$ of robot i is **perfectly known**
- The robots **communicate** with each other
- Each robot is equipped with a **3D range-finding sensor** that it uses to measure the target

Cooperative active target tracking

- The **target** moves in 3D according to the model:

$$\dot{\mathbf{x}}(t) = \mathbf{F}\,\mathbf{x}(t) + \mathbf{G}\,\mathbf{u}(t) + \mathbf{w}(t)$$

  - $\mathbf{x} \in \mathbb{R}^3$: position of the target
  - $\mathbf{u} \in \mathbb{R}^3$: exogenous input
  - $\mathbf{w} \in \mathbb{R}^3$: white Gaussian noise with zero mean and covariance $\mathbf{Q}$

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- **Observation** made by robot i:

$$\mathbf{z}_i(t) = \mathbf{H}_i\,\mathbf{x}(t) + \mathbf{v}_i(t)$$

  - $\mathbf{v}_i \in \mathbb{R}^3$: zero-mean white Gaussian noise
  - Measurement-noise processes of the n robots are *independent*

Cooperative active target tracking

In a standard **3D range-finding sensor** model [Ramachandra, 2000]

$$\mathbf{H}_i = \mathbf{I}_3, \quad i \in \{1, \ldots, n\}$$

and the covariance matrix of $\mathbf{v}_i$ is of the form

$$\mathbf{R}_i^{\mathsf{Car}}(t) \triangleq \mathbf{T}_i(t)\,\mathbf{R}_i(t)\,\mathbf{T}_i^T(t)$$

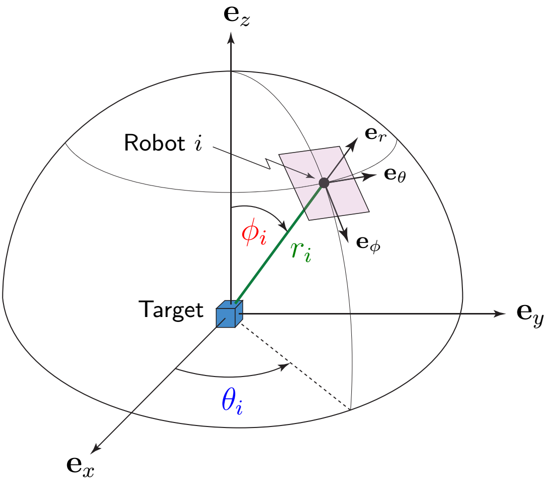
where the rotation matrix

$$\mathbf{T}_i = \mathcal{R}_z(\theta_i)\,\mathcal{R}_y(\phi_i) = \begin{bmatrix} \cos\theta_i\cos\phi_i & -\sin\theta_i & \cos\theta_i\sin\phi_i \\ \sin\theta_i\cos\phi_i & \cos\theta_i & \sin\theta_i\sin\phi_i \\ -\sin\phi_i & 0 & \cos\phi_i \end{bmatrix}$$

and $\mathcal{R}_z(\theta_i)$, $\mathcal{R}_y(\phi_i)$ are the basic 3×3 rotation matrices about the z- and y-axes of an angle θ_i and ϕ_i

Cooperative active target tracking

- **Measurement model: spherical coordinates**



Cooperative active target tracking

$\mathbf{R}_i$ in $\mathbf{R}_i^{\mathsf{Car}} \triangleq \mathbf{T}_i\,\mathbf{R}_i\,\mathbf{T}_i^T$, is the covariance matrix of the measurement noise in the **range-bearing-polar** frame of robot i

$$\mathbf{R}_i = \mathrm{diag}\big(\sigma^2_{\phi_i},\, \sigma^2_{\theta_i},\, \sigma^2_{r_i}\big)$$

where

$$\begin{aligned} \sigma^2_{r_i} &= f_r(r_i) \triangleq a_2(r_i - a_1)^2 + a_0 \\ \sigma^2_{\theta_i} &= f_\theta(r_i) \triangleq \alpha_\theta\, f_r(r_i) \\ \sigma^2_{\phi_i} &= f_\phi(r_i) \triangleq \alpha_\phi\, f_r(r_i) \end{aligned}$$

and a_0, a_1, a_2, α_θ, $\alpha_\phi > 0$

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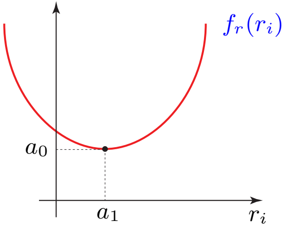
This model assumes the existence of a "**sweet spot**" located at a distance a_1 from the target, where uncertainty in measurements is **minimal**



Cooperative active target tracking

For all $i \in \{1, \ldots, n\}$:

- Target position measurements $\mathbf{z}_i$
- Covariance matrices $\mathbf{R}_i^{\mathsf{Car}}$

are **fused together** to obtain:

- **Global** position estimate of the target $\widehat{\mathbf{x}}_{\mathsf{fus}}$
- **Global** target position-error covariance $\mathbf{P}_{\mathsf{fus}}$

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Goal Control the robots in order to minimize a scalar function of $\mathbf{P}_{\text{fus}}$ (thus reducing the target-estimation error)

Cooperative active target tracking

Cost functions of the most popular **optimum experimental design criteria**:

$J = \ln\det(\mathbf{P}_{\text{fus}})$ D-optimality (determinant) criterion

$J = \text{tr}(\mathbf{P}_{\text{fus}})$ A-optimality (trace) criterion

$J = \lambda_{\text{max}}(\mathbf{P}_{\text{fus}})$ E-optimality criterion

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We can define the **gradient-based control** of robot i as

$$\mathbf{u}_i = -\mathbf{B}\,\mathbf{q}_i - \boldsymbol{\Gamma}\,\mathbf{T}_i \left[\frac{1}{r_i\,\sin\theta_i}\,\frac{\partial J}{\partial \phi_i},\quad \frac{1}{r_i}\,\frac{\partial J}{\partial \theta_i},\quad \frac{\partial J}{\partial r_i} \right]^T$$

where

$\mathbf{B} \succ \mathbf{0}$: damping matrix

$\boldsymbol{\Gamma} \succ \mathbf{0}$: gain matrix

Cooperative active target tracking

Problem How to define $\mathbf{P}_{\text{fus}}$?

Cooperative active target tracking

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- **Instantaneous fusion** of local measurements:

$$\mathbf{P}_{\mathsf{fus}} = \left(\sum_{i=1}^{n} (\mathbf{R}_i^{\mathsf{Car}})^{-1} \right)^{-1}, \quad \widehat{\mathbf{x}}_{\mathsf{fus}} = \mathbf{P}_{\mathsf{fus}} \sum_{i=1}^{n} (\mathbf{R}_i^{\mathsf{Car}})^{-1} \mathbf{z}_i$$

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- Fusion with **Kalman-Bucy filter**:

$$\dot{\mathbf{P}}_{\text{fus}} = \mathbf{F}\,\mathbf{P}_{\text{fus}} + \mathbf{P}_{\text{fus}}\,\mathbf{F}^T + \mathbf{Q} - \mathbf{P}_{\text{fus}}\,\mathbf{C}\,\mathbf{P}_{\text{fus}}$$

$$\dot{\widehat{\mathbf{x}}}_{\text{fus}} = \mathbf{F}\,\widehat{\mathbf{x}}_{\text{fus}} + \mathbf{G}\,\mathbf{u} + \mathbf{P}_{\text{fus}}\,(\mathbf{y} - \mathbf{C}\,\widehat{\mathbf{x}}_{\text{fus}})$$

where

$$\mathbf{C} \triangleq \sum_{i=1}^{n} (\mathbf{R}_i^{\text{Car}})^{-1} \quad , \quad \mathbf{y} \triangleq \sum_{i=1}^{n} (\mathbf{R}_i^{\text{Car}})^{-1} \mathbf{z}_i$$

Cooperative active target tracking

Performance analysis

- Study the role played by:
    - **Sensors' accuracy**
    - **Target's dynamics**

  on the steady-state tracking performance of the coordination strategy

Cooperative active target tracking

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- Analytical bounds on $\mathbf{P}_{\text{fus}}$ can be derived by exploiting the monotonicity property of the RDE arising from the Kalman-Bucy filter

Cooperative active target tracking

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- Extensions:
  - **ACLMT**: "*Active Cooperative Localization and Multi-target Tracking*"
  - **6-DoF quadrotor** model [Gürcüoglu *et al.*, 2013]

Cooperative 3D reconstruction

Goal Build a 3D model of a large-scale *unknown* environment with n cooperating robots

Cooperative 3D reconstruction

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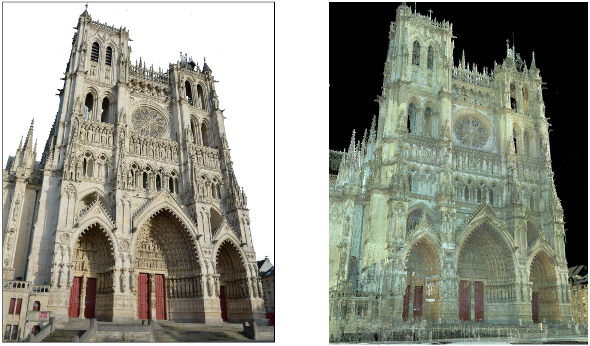
with n cooperating robots

- **Motivation**: programme e-Cathédrale (funding from ScanBot project)
  - `https://home.mis.u-picardie.fr/~ecathedrale`



Real

3D model

Cooperative 3D reconstruction

Assumptions in [Hardouin *et al.*, 2023]:

- Robots equipped with:
    - Sensor which provides depth measurements (e.g. stereo or RGB-D camera)
    - Communication system
    - GNC system: the pose is known (e.g. with VO [Sanfourche *et al.*, 2013])

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Cooperative 3D reconstruction

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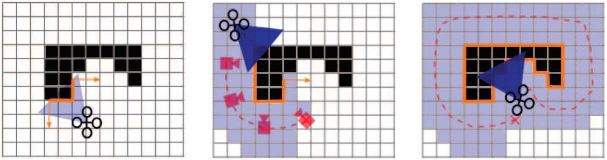
Related work [Bircher *et al.*, 2018], [Song & Jo, 2018]
[Schmid *et al.*, 2020], [Lauri *et al.*, 2020]:

- No check of *completeness* for the generation of new viewpoints
- Only in [Schmid *et al.*, 2020], an *explicit* surface reconstruction
- Except for [Lauri *et al.*, 2020], all methods are *single robot*

Cooperative 3D reconstruction

Next-Best-View planning for online 3D reconstruction:

- Volumetric mapping (implicit surface representation): TSDF
- Surface completeness: ISE (*Incomplete Surface Element*)
    - Roadmap of robot configurations in the free space to scan the ISEs
- Planning according to a surface criterion to perform the reconstruction



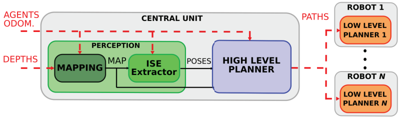
NBV planning for surface inspection via volumetric mapping

Cooperative 3D reconstruction

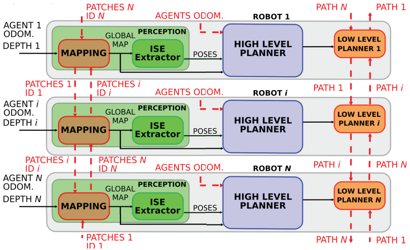
TSGA (TSP-Greedy Allocation) planner:

- **High-level**: Greedily assign the sequence of viewpoints to the robots by iteratively solving a *maxATSP*
- **Low-level**: Compute the path in the free space using a Probabilistic Roadmap planner (LazyPRM*)

dist-TSGA: Decentralized version of TSGA



Centralized architecture

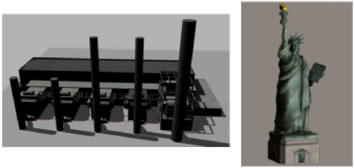


Decentralized architecture

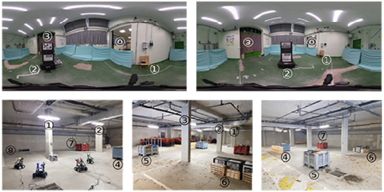
Cooperative 3D reconstruction

Simulations (ROS/Gazebo)

- 1, 3 and 5 hexarotors with 4 DoFs
- Benchmark environments:
  - *Powerplant*
  - *Statue of Liberty*



Video



Experiments

- Centralized architecture: from 1 to 4 Wifibots
- Decentralized architecture: 2 Wifibots
- Environments:
  - *Test arena*: 8 × 7 × 2 m^3
  - *Parking lot*: 21 × 14 × 2 m^3

Communication graph: beyond the Laplacian

- $\mathbf{L} = \mathbf{D} - \mathbf{A}$ (Laplacian)
- $\mathbf{Q} = \mathbf{D} + \mathbf{A}$ (Signless Laplacian [Cvetković *et al.*, 2007])
- $\mathbf{L}_p(s) = \mathbf{D} - s\mathbf{A},\ s \in \mathbb{R}$ (Parametric Laplacian [Morbidi, 2014])
- $\mathbf{A}_\alpha = \alpha\,\mathbf{D} + (1-\alpha)\mathbf{A},\ \alpha \in [0,\,1]$ [Nikiforov, 2017]
- $\boldsymbol{\Delta}(s) = \mathbf{I}_n - s\mathbf{A} + s^2(\mathbf{D} - \mathbf{I}_n),\ s \in \mathbb{R}$ (Deformed Laplacian [Morbidi, 2013])
- $\boldsymbol{\gamma}(\mathbf{A},\,\mathcal{S}) = m_1\mathbf{D}_a^{e_1} + m_2\mathbf{D}_a^{e_2}\,\mathbf{A}_a\,\mathbf{D}_a^{e_3} + m_3\mathbf{I}_n,$
  $\mathbf{D}_a = \mathbf{D} + a\mathbf{I}_n,\ \ \mathbf{A}_a = \mathbf{A} + a\mathbf{I}_n,\ \ \mathcal{S} = \{m_1, m_2, m_3, e_1, e_2, e_3, a\}$
  (Parametrised GSO [Dasoulas *et al.*, 2021])
- $f(\mathbf{L})$ (Function of Laplacian [Morbidi, 2022])

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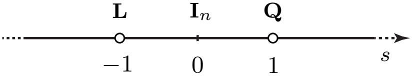
Deformed consensus

- Remark: $\mathbf{\Delta}(1) = \mathbf{L}$ and $\mathbf{\Delta}(-1) = \mathbf{Q}$



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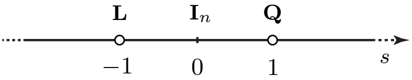

Problem Study the stability properties of the system [Morbidi, 2013]:

$$\boxed{\dot{\mathbf{x}}(t) \;=\; -\mathbf{\Delta}(s)\,\mathbf{x}(t),\;\; s \in \mathbb{R}}$$

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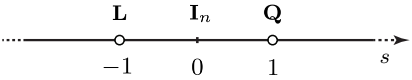

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Link with **QEP** (Quadratic Eigenvalue Problem) [Tisseur & Meerbergen, 2001]

Deformed consensus

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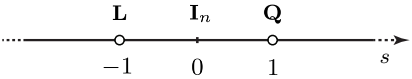


Problem Study the stability properties of the system [Morbidi, 2013]:

$$\boxed{\dot{\mathbf{x}}(t) \;=\; -\mathbf{\Delta}(s)\,\mathbf{x}(t),\;\; s \in \mathbb{R}}$$

Link with **QEP** (Quadratic Eigenvalue Problem) [Tisseur & Meerbergen, 2001]

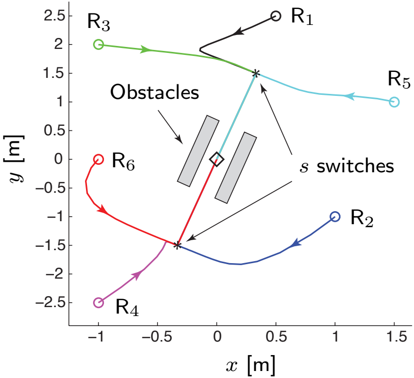
The deformed Laplacian has recently found application in:

- **Semi-supervised learning** [Gong *et al.*, 2015]
- Design of **centrality measures** for (un)directed networks [Grindrod *et al.*, 2018], [Arrigo *et al.*, 2018, 2019, 2020]

Deformed consensus

Example

- Communication graph: $\mathcal{G} = P_6$
- Six robots rendezvous at $(0, 0)$ and avoid two obstacles
- $-1 \xrightarrow{s} 0$ (from a marginally- to an asymptotically-stable equilibrium point)



Function of Laplacian

Problem Find the functions $f(\mathbf{L})$ that preserve the structure of $\mathbf{L}$

- $f(\mathbf{L})$ must be *positive semidefinite*
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- Consensus value is left *unchanged* (f-invariance)
- Advantage: *design flexibility*
- Is the *sparsity pattern* of $\mathbf{L}$ preserved in $f(\mathbf{L})$? It is not, in general. But . . .

Function of Laplacian

Numerical simulations

Shape-based formation control for single-integrator robots:

$$\boxed{\dot{\mathbf{x}}(t) = (-f(\mathbf{L}) \otimes \mathbf{I}_2)(\mathbf{x}(t) - \boldsymbol{\xi})}$$

$\boldsymbol{\xi} \in \mathbb{R}^{2n}$: vector of target positions [Mesbahi & Egerstedt, 2010]

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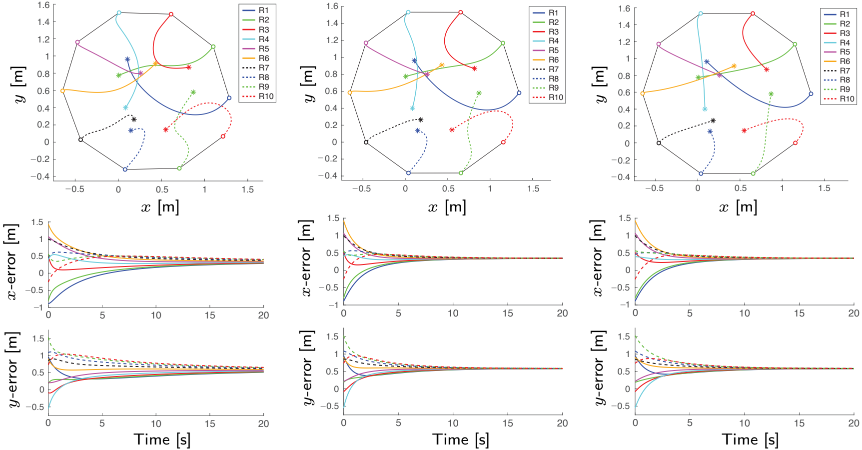
Example

- $\mathcal{G} = P_{10}$, $\boldsymbol{\xi} =$ vertices of a regular decagon
- Comparative analysis:
  - $f(\mathbf{L}) = \mathbf{L}, \quad f(\mathbf{L}) = \log(3\mathbf{L} + \mathbf{I}_{10}), \quad f(\mathbf{L}) = \mathbf{I}_{10} - e^{-3\mathbf{L}}$
  - Fiedler values:
    $\lambda_2 \simeq 0.0979, \quad \log(3\lambda_2 + 1) \simeq 0.2575, \quad 1 - e^{-3\lambda_2} \simeq 0.2545$
- Formation error: $\boldsymbol{e}(t) = \mathbf{x}(t) - \boldsymbol{\xi}$

Function of Laplacian

$f(\mathbf{L}) = \mathbf{L}$ $\quad$ $f(\mathbf{L}) = \log(3\mathbf{L} + \mathbf{I}_{10})$ $\quad$ $f(\mathbf{L}) = \mathbf{I}_{10} - e^{-3\mathbf{L}}$



Outline

- Part I
  - Academic background
  - Research projects
  - Professional and teaching activities

- **Part II**
  - Multi-robot systems: generalities
  - Formation control of mobile robots
  - Coordinated control of multi-robot systems
  - **Conclusion and future research**
  - Acknowledgements

Conclusion

- **Formation control of mobile robots**
  - Favorite research topic since 2005
  - Inclusion of additional constraints:
    - Kinematic constraints of the robots
    - Visibility/connectivity constraints
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- **Coordinated control of multi-robot systems**
  - New distributed algorithms for a team of UAVs:
    - Environmental monitoring
    - Active target tracking
    - 3D reconstruction
  - Communication graph: beyond the Laplacian
    - Deformed Laplacian $\mathbf{\Delta}(s)$
    - Function of Laplacian $f(\mathbf{L})$

Future research

Collision avoidance is an essential prerequisite, **but** . . .

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- Robots have **limited sensing** and **communication capabilities**
- Robots may have **restricted mobility**
- Workload should be **equally balanced**
- Coordination strategy: **scalable**, **resilient** and **robust** to disturbances
- Multi-robot system should always remain **safe**
- Cooperative task may include **temporal/logic constraints**
    - **Asynchronous communication** is sometimes the only option
- Robots have strict requirements in terms of **energy storage**
- Robots may exhibit different sources of **heterogeneity**:
    - Type of locomotion: ground, aerial, surface and underwater robots
    - Role within the team: e.g. leader-follower model
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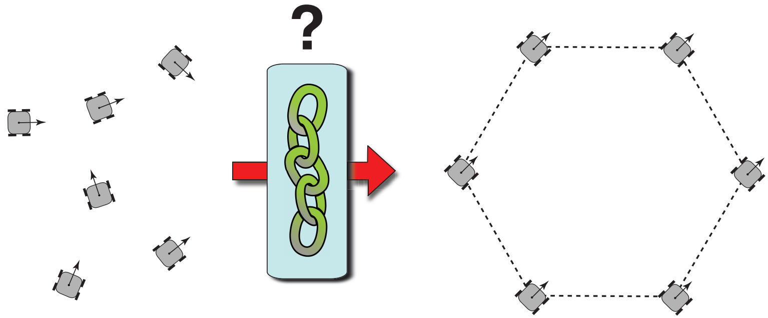
Future research

1. A **general formulation** encompassing the previous (conflicting) requirements is still missing
    - What is its *nature* and *complexity*?



Future research

2. Which tasks are amenable to a **distributed implementation**?
   - ◦ Generalized (Hölder) means [Bauso *et al.*, 2006], [Cortés, 2008]:

$$M_p(x_1, \dots, x_n) = \left(\frac{1}{n} \sum_{i=1}^{n} x_i^p \right)^{\frac{1}{p}}, \; p \in \mathbb{R} \setminus \{0\}, \;\; x_i > 0$$

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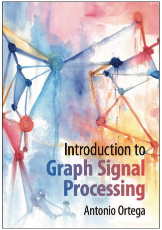
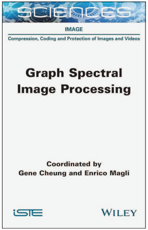
3. Emergence of **graph signal processing** and its ramifications (e.g. in image processing and machine learning with **GNN**)
   - Many connections to explore with *consensus theory* [Kortvelesy & Prorok, 2021], [Gama *et al.*, 2022], [Marino *et al.*, 2023]




SCIENCES

IMAGE

Compression, Coding and Protection of Images and Videos

Graph Spectral Image Processing

Coordinated by
Gene Cheung and Enrico Magli

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Future research

4. **New sensing modalities**
    - Event cameras
        - Mono and stereo (CERBERE and EVELOC projects): PhD of D. Rossi and A. El Moudni
        - Omnidirectional, mono and stereo (EVENTO and DEVIN projects): PhD of D. Rodrigues da Costa
    - Twin-fisheye cameras (ADAPT project, PanoraMIS dataset)

Future research

4. **New sensing modalities**
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   - Twin-fisheye cameras (ADAPT project, PanoraMIS dataset)
5. **Mixed human-robot teams**
   - Which is the most *effective* and *intuitive* means of communication between humans and robots?

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I am very grateful to:

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Jordan

Guillaume

Devesh

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