Decisional issues in multi-UAV systems

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Lakeside Lab research days on multi-UAV systems,
Klagenfurt, Austria (July 2013)

Where do I come from?

Robotics at LAAS/CNRS, Toulouse, France

A keyword: **autonomy**

- Research topics
  - Perception, planning and decision-making, control
  - Plus: control architecture, interactions, ambient intelligence systems, learning

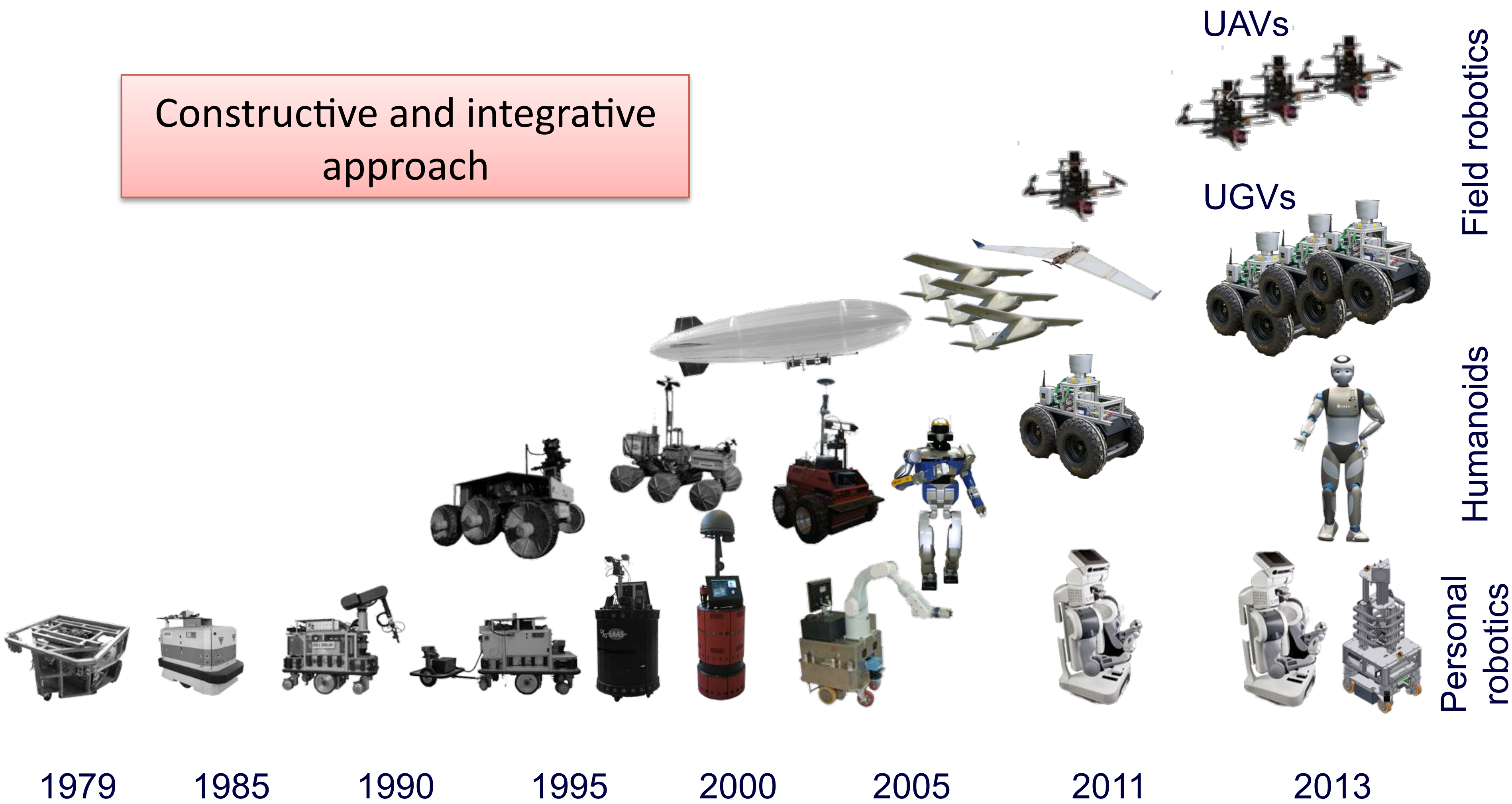
- Research domains
  - Cognitive and interactive Robotics
  - Aerial and Terrestrial Field Robotics
  - Human and anthropomorphic motion
  - Bio-informatics, Molecular motion

3 research groups :
12 full time researchers
10 university researchers
4 visitors
50 PhD students
10 post-docs

- Considered applications: Planetary exploration, Service and personal robotics, virtual worlds and animation, biochemistry, embedded systems, transport, driver assistance, defense, civil safety

Robotics @ LAAS-CNRS

Constructive and integrative approach



Open source software tools: www.openrobots.org

On autonomy

au•ton•o•mous |ôˈtänəməs|

adjective

(of a country or region) having self-government, at least to a significant degree : *the federation included sixteen autonomous republics.*

- acting independently or having the freedom to do so : *an autonomous committee of the school board | autonomous underwater vehicles.*
- (in Kantian moral philosophy) acting in accordance with one's moral duty rather than one's desires.

DERIVATIVES

au•ton•o•mous•ly adverb

ORIGIN early 19th cent.: from Greek ***autonomos*** ***'having its own laws'*** + -ous .

On autonomy

➡ Notion of *dependence*

- Dependance on the humans
  - Command
  - Skilled operators
  - Lambda users
- Dependence on the infrastructure
  - Abandonned sensors
  - Localisation
  - Communication
  - Databases (géographic, semantic, …)
  - …
- Dependence on the other robots

➡ Autonom<u>ies</u> :

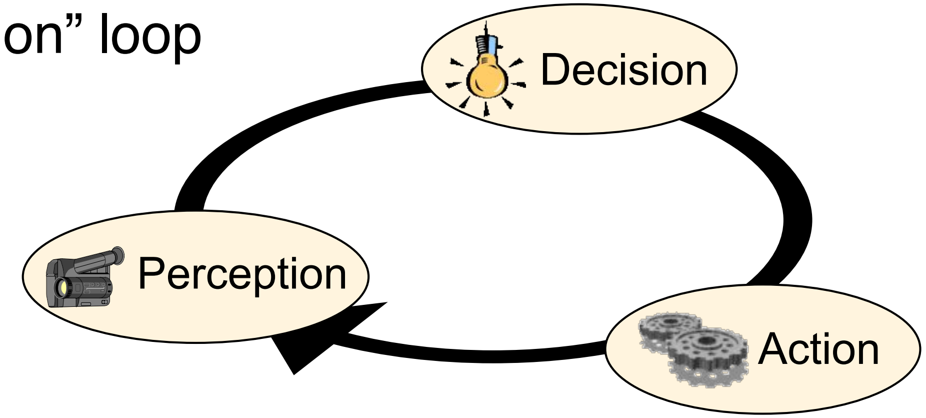
- Power autonomy
- Execution control autonomy (rather "automatic control")
- Navigation autonomy
- <u>Decisional autonomy</u>

From automatic control to autonomous control

- Automatic control :
  - Well defined task *("regulate variable", "follow trajectory"…)*
  - "Direct" link between perception and action
  - Environment well modeled

- Autonomous control :
  - More general task *("reach position", "monitor area "…)*
  - Environment mostly "unknown", variable…
  - Calls for *decisional processes*

  ⇒ "perception / Decision / Action" loop



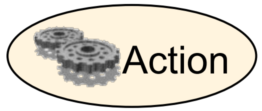
Plus :
- Processes *integration*
- Learning
- Interaction with humans
- Interactions with other robots
- …

Autonomy

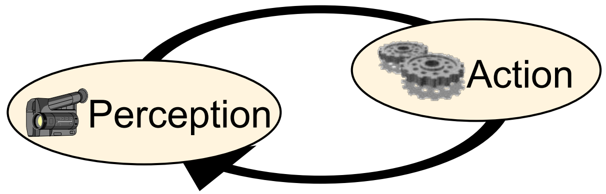
E.g. for a drone:

– Regulate heading / speed / altitude

– Follow a list ordered waypoints

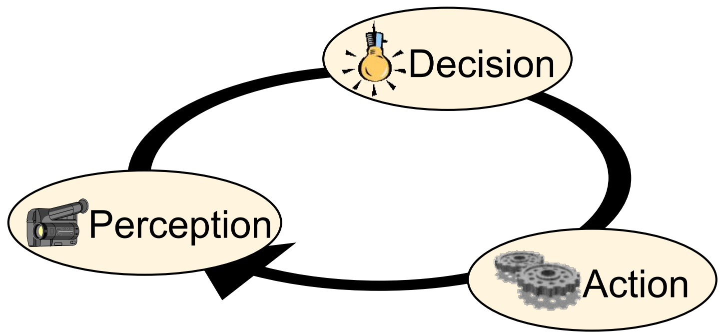


– Follow a geometric trajectory



– Follow a road

– Follow a target



– Survey an area while avoiding threats and obstacles

"Decision": notion of deliberation, planning, prediction and evaluation of the outcomes of an action

On the importance of *models* for Autonomy

Planning = Simulation + Search

- Simulation of the effects of an action with a predictive model
- Search over possible organizations of possible actions to meet a goal or to optimize a criteria

Illustration: autonomous rover navigation

Simple instance of a perception / decision / action loop:

- Gather data on the environment, structure it into a model
- Plan the trajectory to find the “optimal” one
- Execute the trajectory

On the importance of *models* for Autonomy

Planning = Simulation + Search

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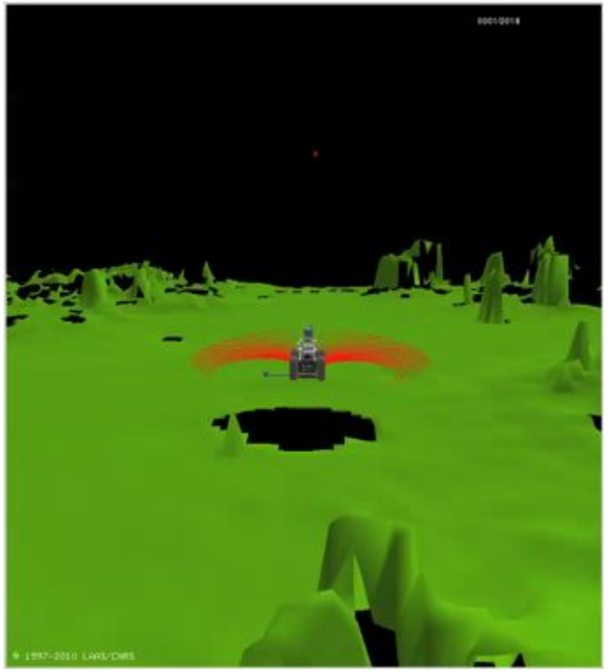
Illustration: autonomous rover navigation



Simulation = convolution of action and environment models

Environment models:

- at the heart of autonomy
- at the heart of cooperation

Multiple robots call for more autonomy

Main drivers for autonomy

- Dirty, Dull, Dangerous tasks
- Operations in remote areas
- Allows the deployment of complex systems
- Money savings !

Multiple robotics systems

- Are inherently more complex
- Call for new specific processes :
    - Cooperation
    - Task allocation
    - Task coordination
- Implies new decisional architectures

Outline

Notion of Autonomy

Multiple UAVs in the sky

Multiple UAV/UGV systems

Current projects

Multiple UAVs in the sky

Environment model ? an empty space !

(possibly with a non uniform atmospheric flow field)

➡ Allows for “easy” development at the core of decision

Example 1: “Monitoring a set of locations” mission

➡ For a fleet of UAVs, mainly a *task allocation* problem: which UAV will observe which location?

The task allocation problem

The "canonical" task allocation problem:

- Given:
  - A set of robots $\{R\}$
  - A set of tasks $\{T\}$
  - A cost function $c:\{R \times T\} \rightarrow \Re^{+} \cup \{+\infty\}$
- Find the allocation A^{*} that minimizes the cost sum (or the max. of individual costs, or the individual cost repartition, or…)

A well-known and well-posed problem (also name "optimal allocation problem) – but highly combinatorial

Main approaches:

- Centralized : optimization (MILP), genetic algorithm, simulated annealing
- Distributed :
  - DCOP, distributed protocols
  - Negotiation-based approaches: market-based approaches

Market based task allocation

Auctions (tasks) are published, robots bid, the "best" bidder gets the task

Basic functions required

- Ability to bid: task insertion cost evaluation
- Auctioning strategies: who places auctions ?
- Overall objective function to minimize

Many possibilities for each function, *e.g.*:

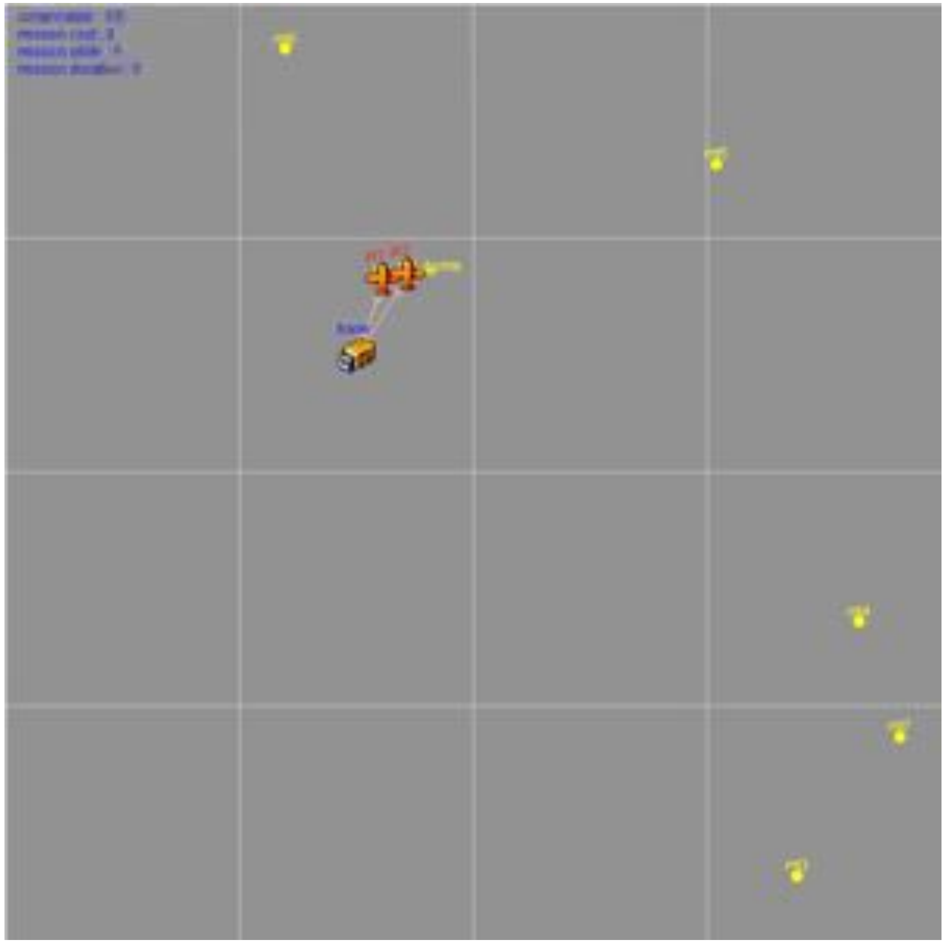
- Task insertion
  - From a simple cost addition…
  - … to a (complex) plan update
  - Mix costs, risks, utilities…
- Auctioning strategies
  - Centralized vs. bidders can emit auctions
  - When to close the market ?
  - Auctions can concern a set of tasks…
- Objective function
  - Sum of individual costs, dispersion of individual costs, max of individual costs…

B. Dias "Market-Based Multirobot Coordination: A Survey and Analysis" 2006

Market based task allocation

Illustration 1: the Multiple travelling salesman problem

- White dot = auction token
- Simple task insertion
- The cost includes an “equity” constraint
- All tasks are allocated before moving
- All robots must fly back home



Market based task allocation

Main features of market-based approaches

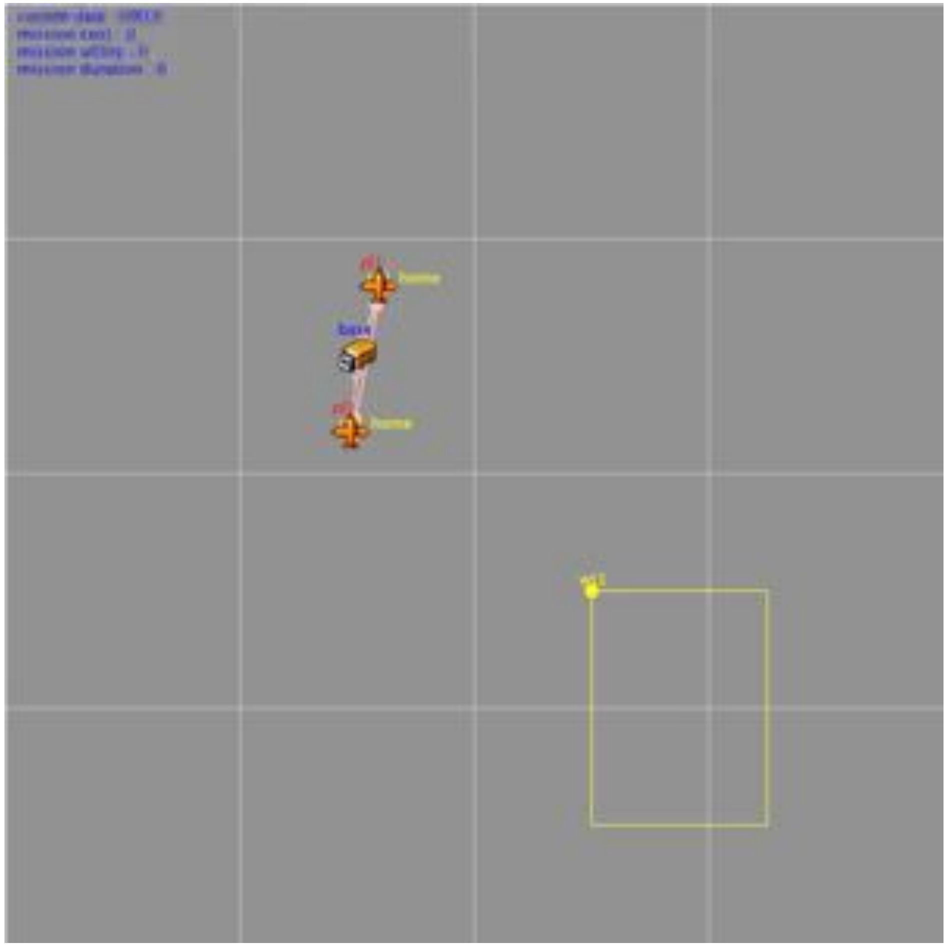
- A simple protocol, applicable to a wide variety of complex problems
- Can be distributed (can bear with communication constraints)
- Can handle dynamic events:
    - Robot failures
    - Unexpected events
    - New tasks

- No guarantee on any optimality

Satisfying communication constraints

- One single “survey” task (= square pattern)

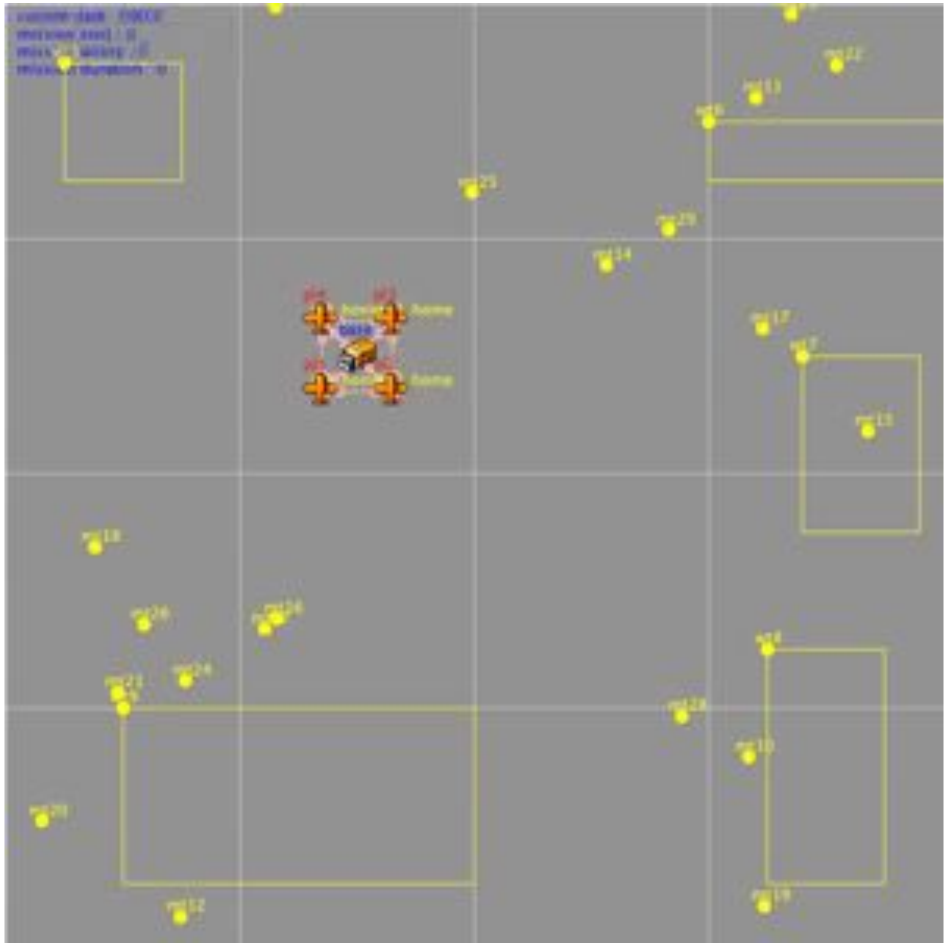
- The constraint satisfaction yields new tasks (“com relay”)



Satisfying communication constraints

Illustration: multi TSP + several constrained “survey” tasks

- 4 robots
- 5 survey tasks
- 18 places to visit



Multiple UAVs in the sky

Environment model ? an empty space !

(possibly with a non uniform atmospheric flow field)

➡ Allows for "easy" development at the core of decision

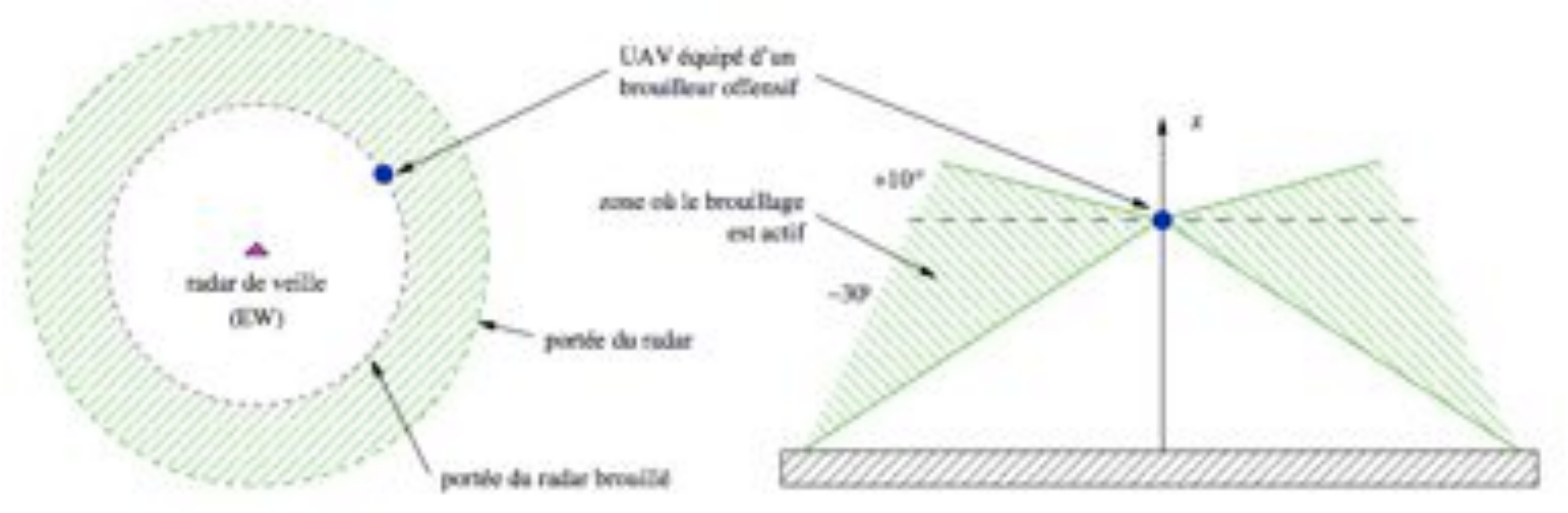
Example 2: "Fly a flock of drones amidst threats"

➡ For a fleet of UAVs, again mainly a *task allocation* problem: which UAV will jam a threat / protect others?

Fly a flock of drones amidst threats

Given:

- A convoy mission planned on a map of known threats (EW radars) – there are unknown threats (TF radars)
- A fleet of *heterogeneous* UAVs
    - Some are equipped with EW jammers
    - Some are equipped with defence against TF jammers



Geometry of EW jammers

Fly a flock of drones amidst threats

Given:

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  - Some are equipped with EW jammers
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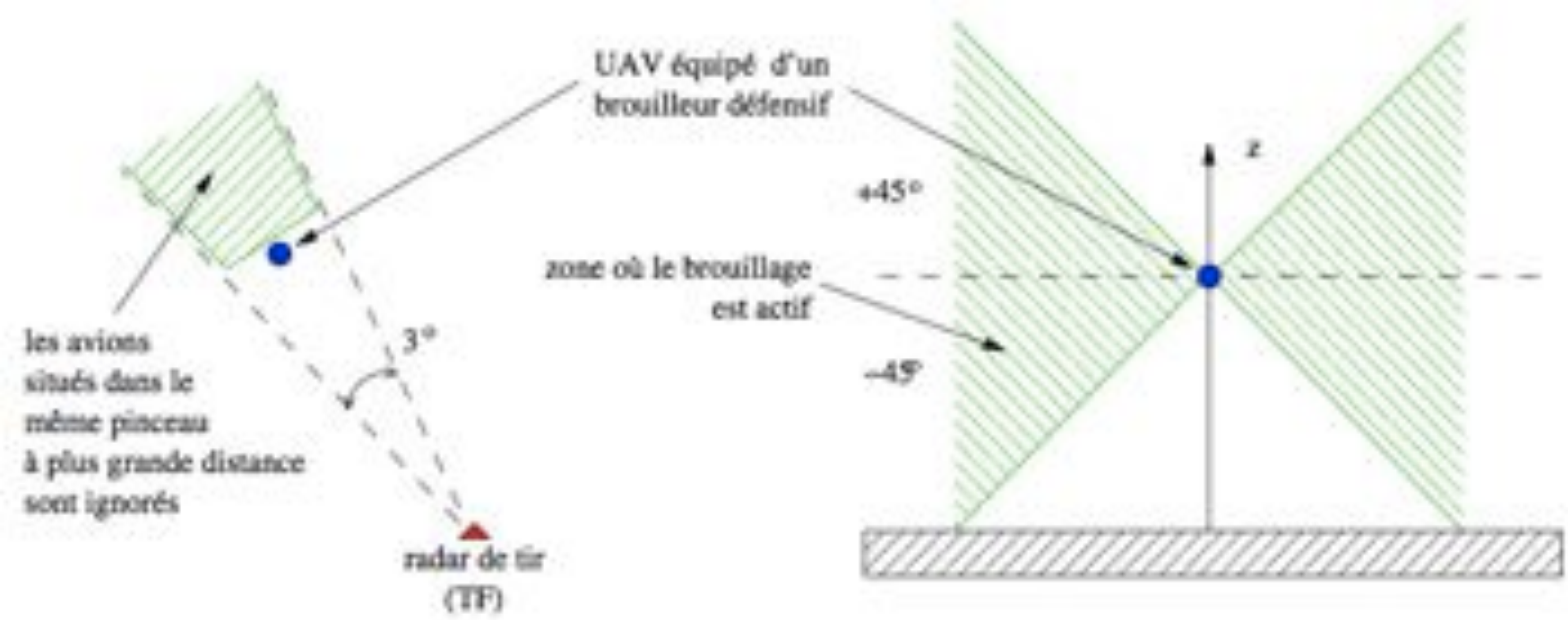


Geometry of TF jammers

Fly a flock of drones amidst threats

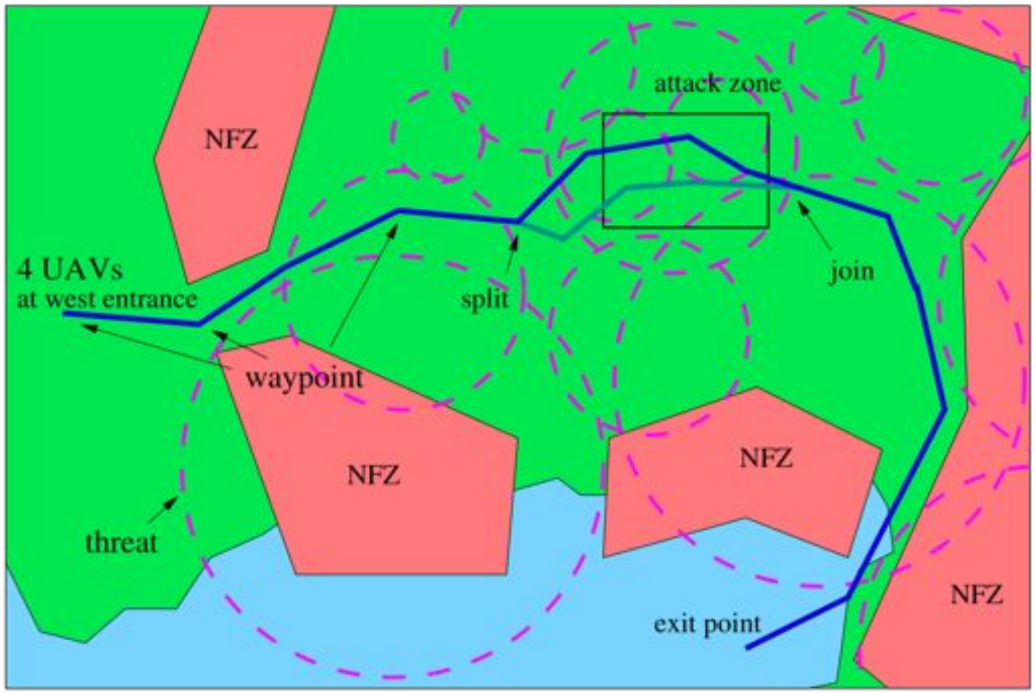
Given:

- A convoy mission planned on a map of known threats (EW radars) – there are unknown threats (TF radars)
- A fleet of *heterogeneous* UAVs
  - Some are equipped with EW jammers
  - Some are equipped with defence against TF jammers

Fly safely the fleet (“Formation-less formation flight”) though the route

- Define the optimal configuration (“formation”) of UAVs

- Manage configuration transitions



Fly a flock of drones amidst threats

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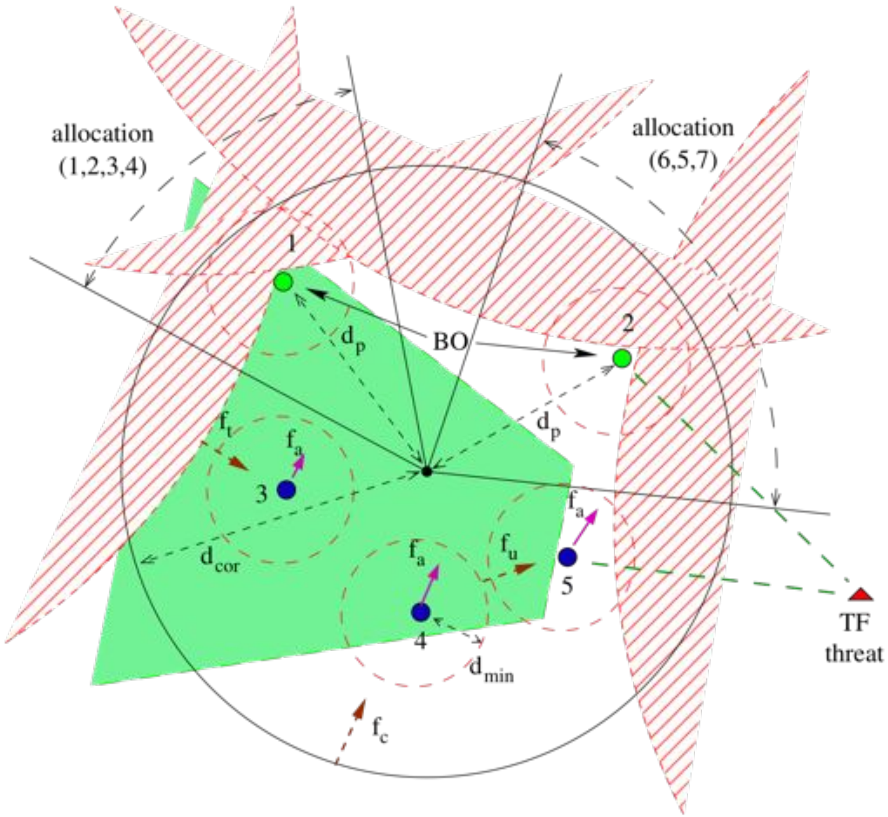
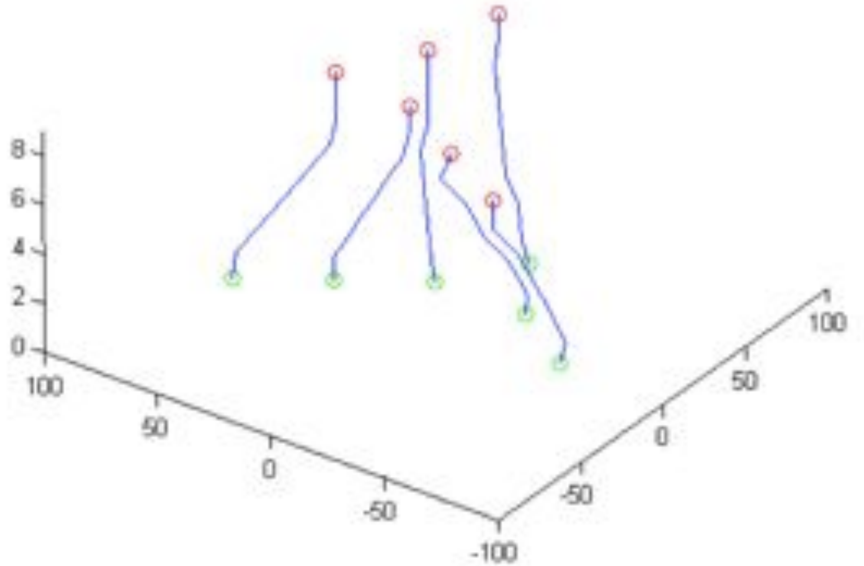




Fly a flock of drones amidst threats

Illustration

Outline

Notion of Autonomy

Multiple UAVs in the sky
- Monitoring a set of locations
- Fly a flock of drones amidst threats

Multiple UAV/UGV systems

Current projects

Context: teams of AGVs/UGVs

Where and what for?



Dozens of *heterogeneous* robots *cooperate* to achieve *long-lasting* missions in *large* environments

Considered missions:

- observations, scene analyses, situation assessments
- *interventions* in the environment

In various application contexts:

- Environment monitoring (pollutions, science, …)
- Search and rescue
- Defense applications, Civil security

Where and what for?

Dozens of *heterogeneous* robots *cooperate* to achieve
long-lasting missions in *large* environments

Large scale (*km*^{3}) implies:

- Faster robots, longer missions (“lifelong autonomy”)
- Communication constraints
- Large (mutli-scale) environment models

1. Planning a surveillance mission

Given:

- A team of robots

- An environment to monitor

- A set of constraints to satisfy (*e.g.* communications)

➡ Find the (optimal) trajectories to observe the whole environment

1. Planning a surveillance mission

Given:

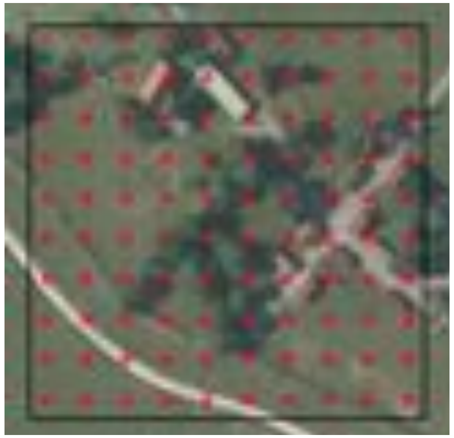
- A team of robots
- An environment to monitor
- A set of constraints to satisfy (*e.g.* communications)

Actions to plan:

- Observation tasks (hence motion tasks)
- Communications

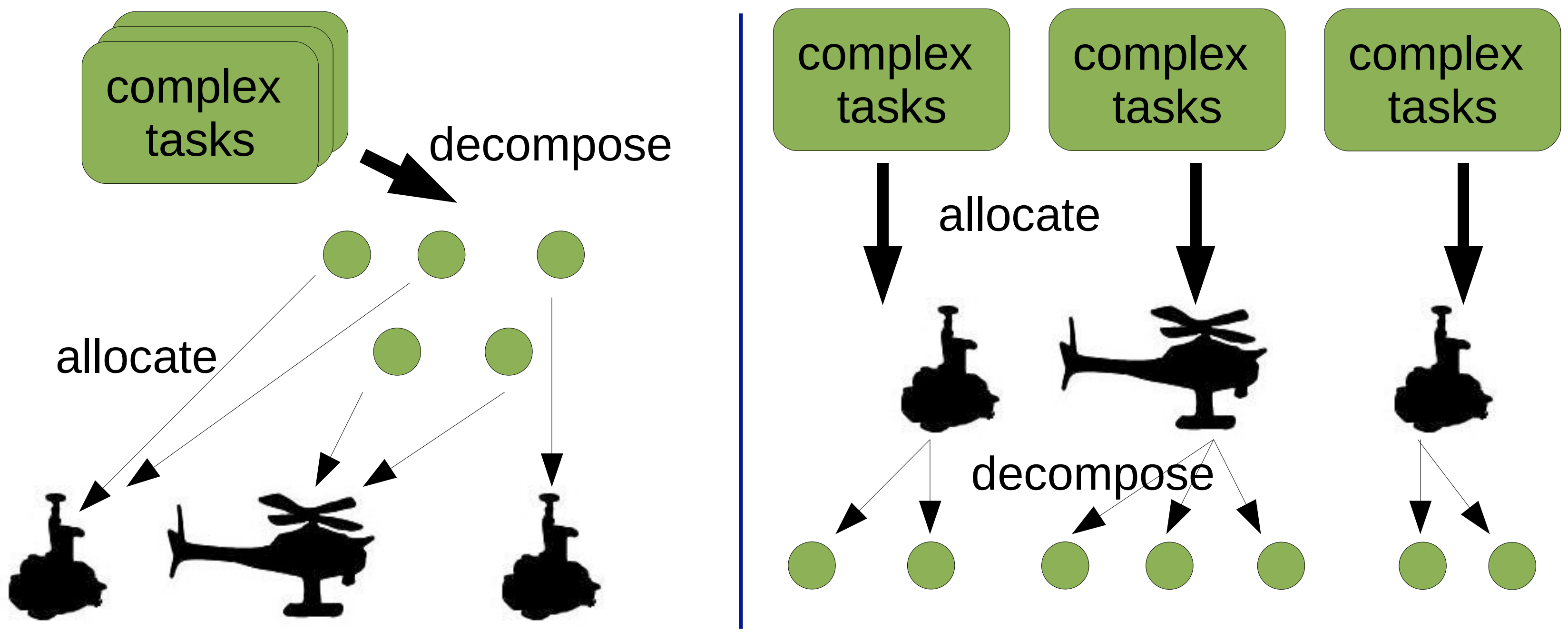
Approach:

- A task allocation process (distributed market-based approach)
- Large scale: necessity to interleave allocation and decomposition processes



1. Planning a surveillance mission

The overall mission is not necessarily expressed as a set of elementary tasks: it has to be decomposed/refined



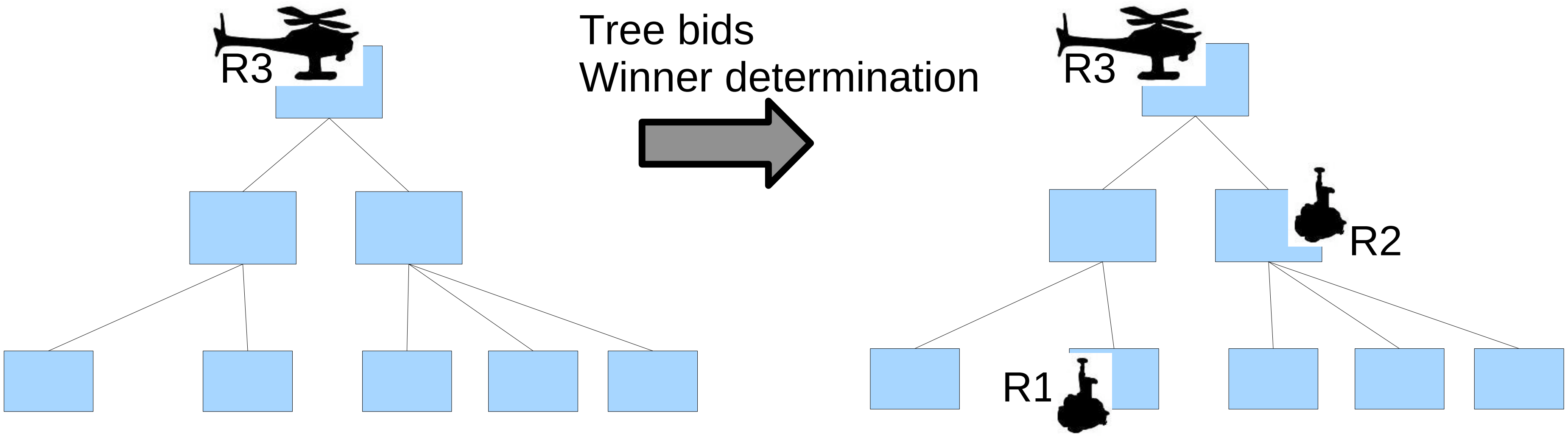
Decompose then allocate

Allocate then decompose

1. Planning a surveillance mission

Decomposition made according to a Hierarchical Task Network scheme (HTN)

- Breaks down the planning complexity
- Allows auctions on variable complexity structures



1. Planning a surveillance mission

2. Navigating a rover in an unknown environment

Given:

- A team of robots

- An unknown environment

- A set of constraints to satisfy (*e.g.* communications)

➡ Find the (optimal) trajectory for the rover to reach a given goal

2. Navigating a rover in an unknown environment

Given:

- A team of robots
- An unknown environment
- A set of constraints to satisfy (*e.g.* communications)

Actions to plan:

- Environment modelling tasks
- Rover Motions
- Communications

Approach:

- The UAV serves the UGV, by providing *traversability maps*
- Find the areas to perceive relevant for the mission

2. Navigating a rover in an unknown environment

(simulation with http://morse.openrobots.org)

Decision and environment models

Planning = Simulation + Search

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Decision and environment models

Planning = Simulation + Search

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	Surveillance	Rover navigation
Simulation	• Environment observations • Motions • Communications	• Environment modeling • Motions • Communications
Search	Task allocation scheme	Heuristic graph search

Simulation = convolution of action and environment models → Environment models:
- at the heart of autonomy
- at the heart of cooperation

Decision and environment models

Planning = Simulation + Search

- Simulation of the effects of an action with a predictive model
  ➞ by "convolving" action models with environment models

What are the actions to plan / decide?

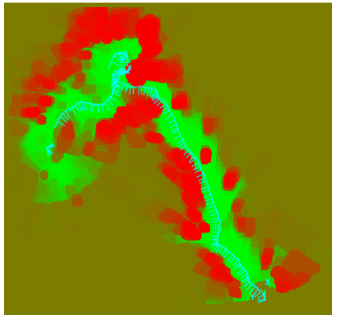
- Motions
- Environment observations (payload)
- Communications (within robots, with the control station)

- Localization
- Environment perception and modeling

Decision and environment models

Planning motions

- At a coarse level (itinerary)
  ➞ notion of traversability
  (geometry, terrain nature)



Decision and environment models

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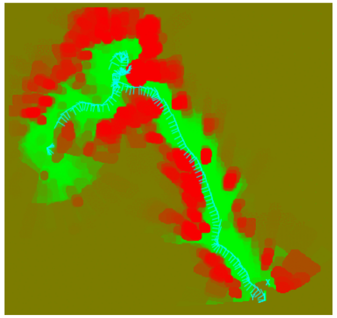
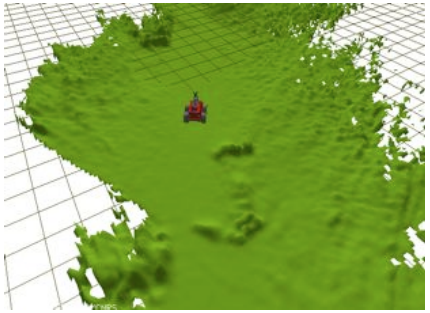


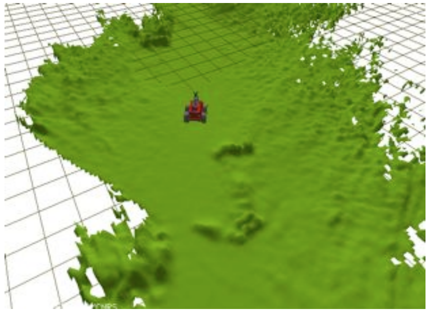
- At a fine level
  ➞ geometry, terrain nature (Digital Terrain Map)



Decision and environment models

Planning observations

- Need to predict visibilities
  ➞ geometry (2.5D or 3D)



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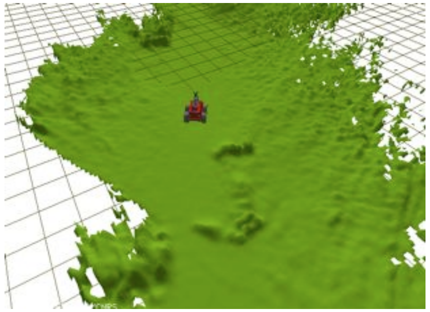
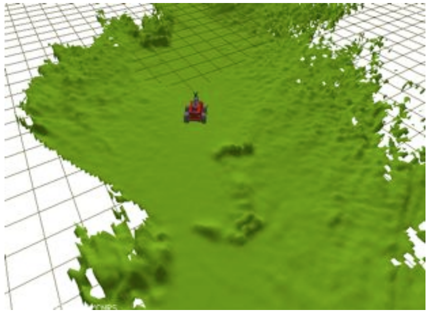


Planning communications

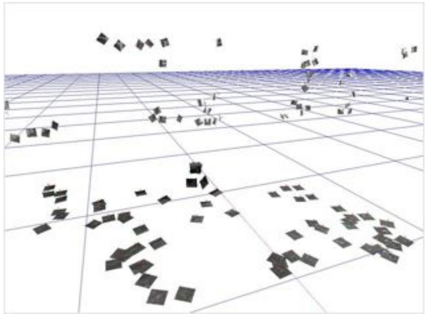
- Need to predict radio visibilities
  ➞ geometry, physical properties

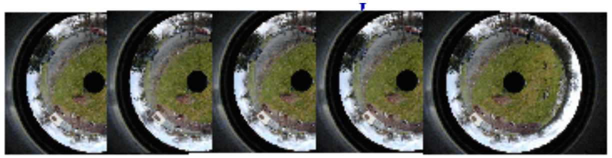


Decision and environment models

Planning localization

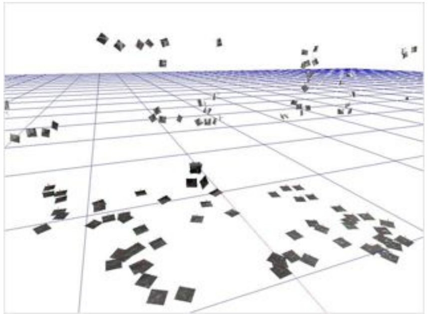
- GPS coverage
- INS / Odometry: terrain nature
- Exteroceptive sensors: landmarks or other models (geometry, appearance models, …)





Decision and environment models

Planning localization



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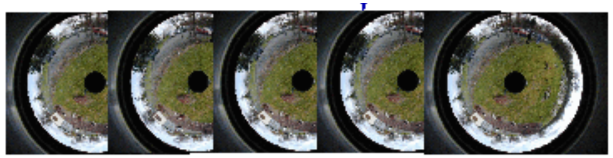
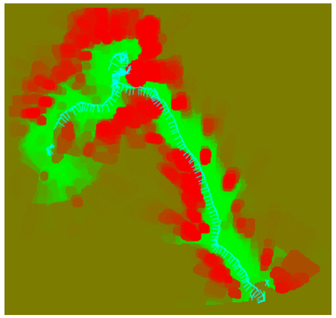
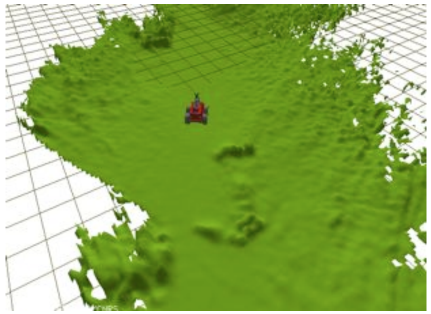


Planning environment perception & modeling

- Need to predict the *information gain*

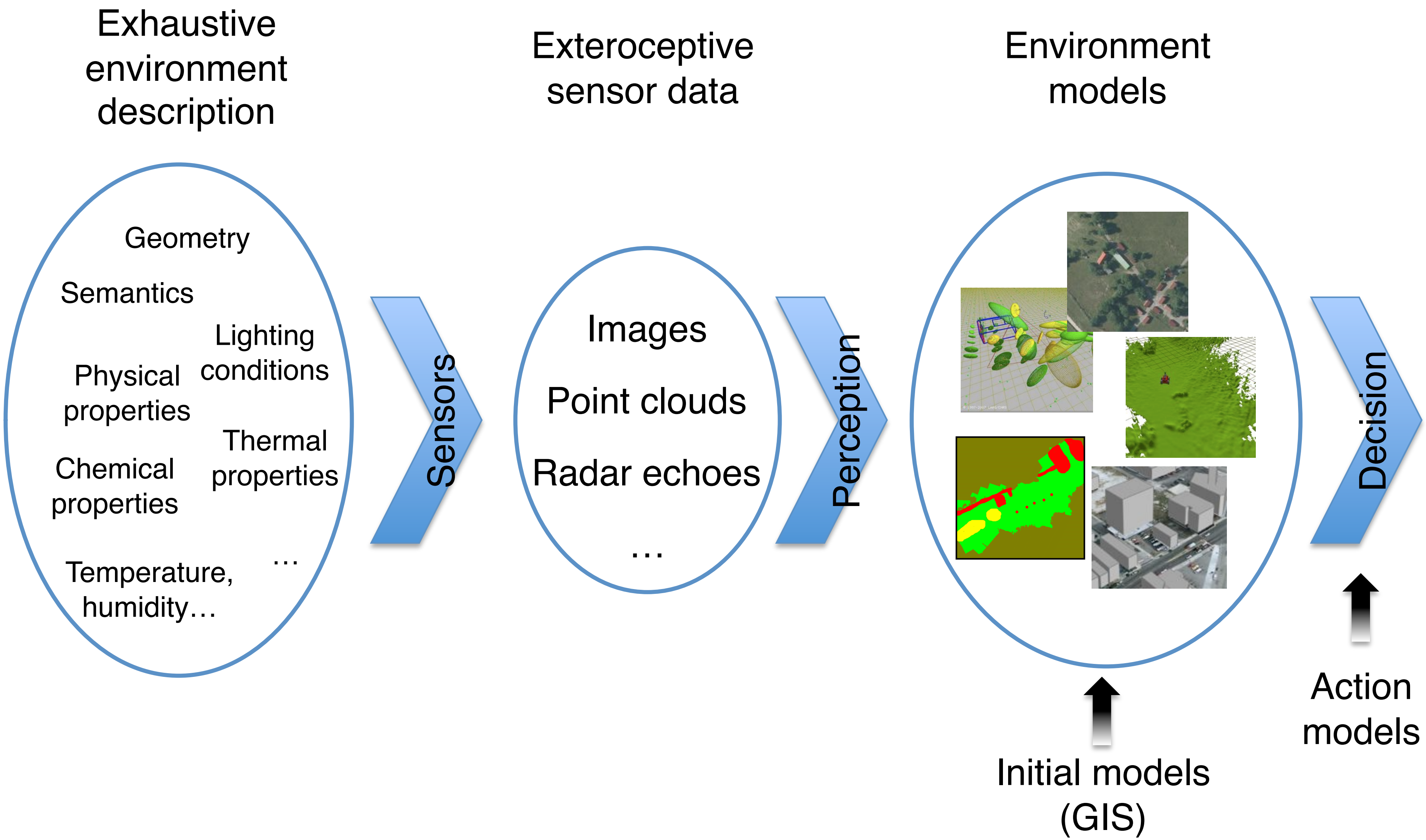
  ➞ amount of information in the environment models (uncertainty, entropy…)





A database of environment models

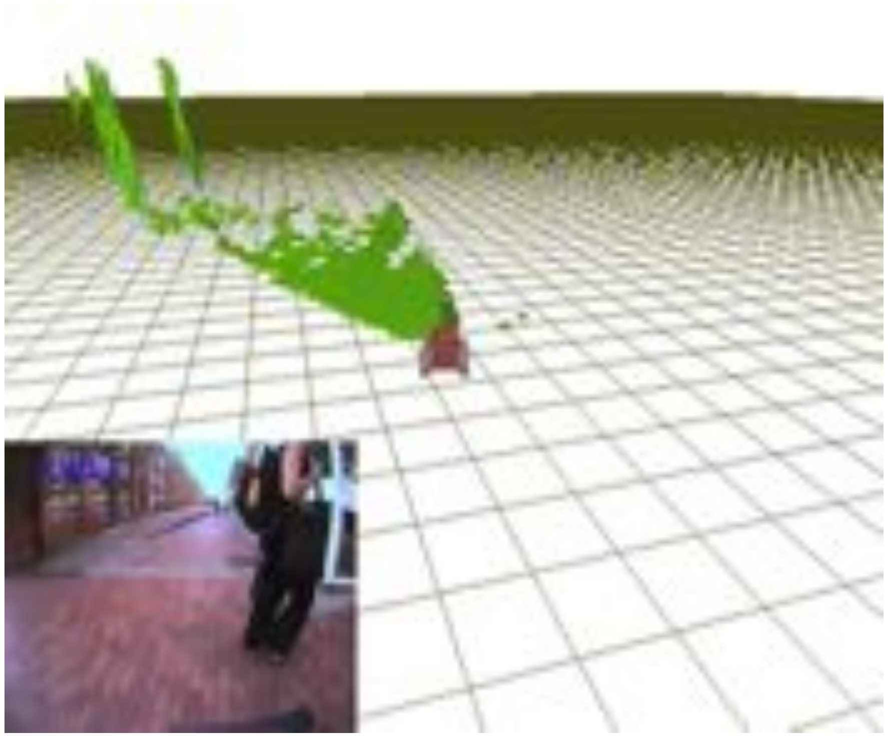
Building envt. models: information flow



Building a digital terrain model

With a rover, using point clouds (here stereovision)

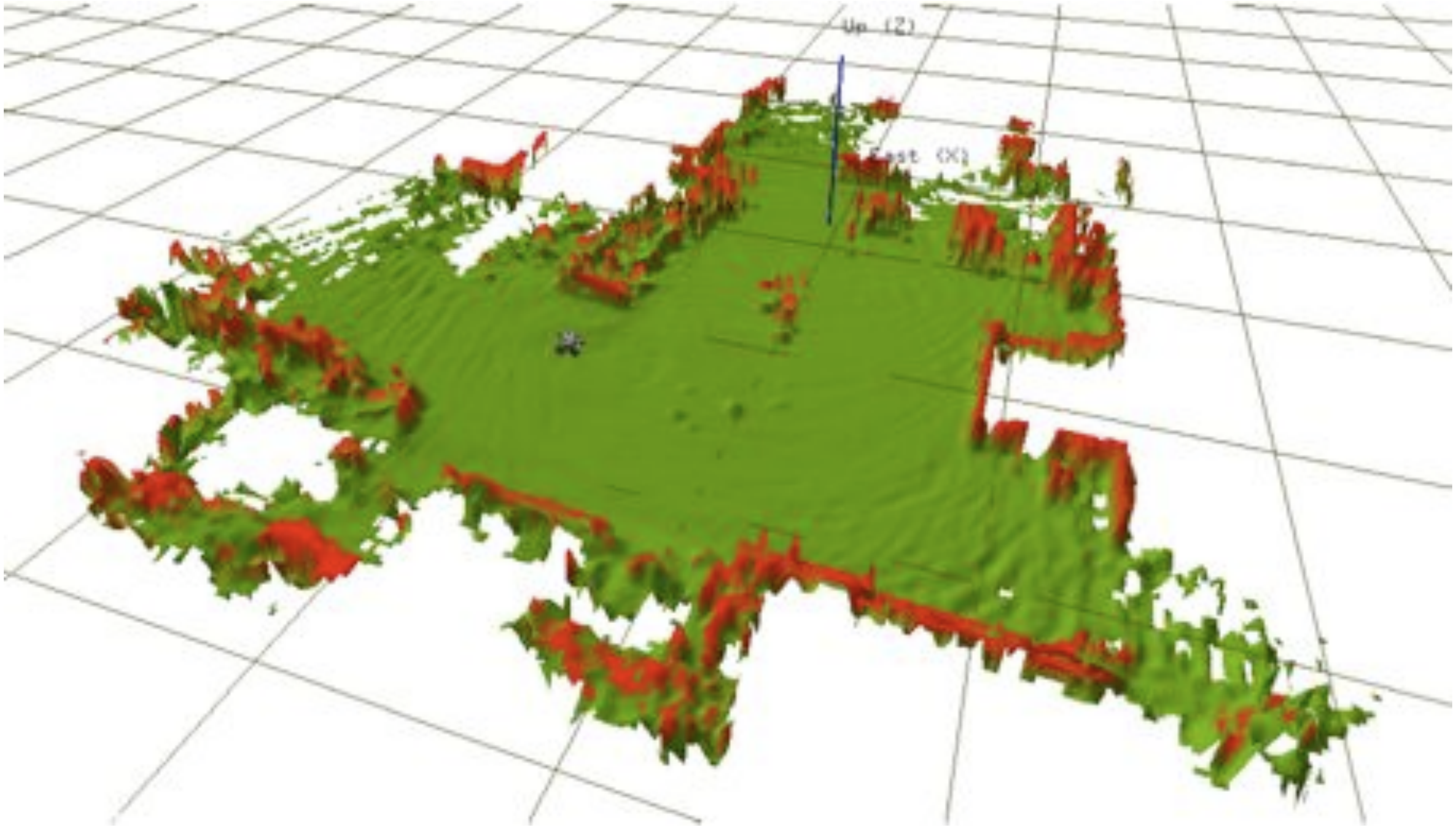
Resampling data to obtain a *z=f(x,y)* representation on a regular Cartesian grid



Building a digital terrain model

With a rover, using point clouds (here Velodyne Lidar)

Resampling data to obtain a $z=f(x,y)$ representation on a regular Cartesian grid



Building a digital terrain model

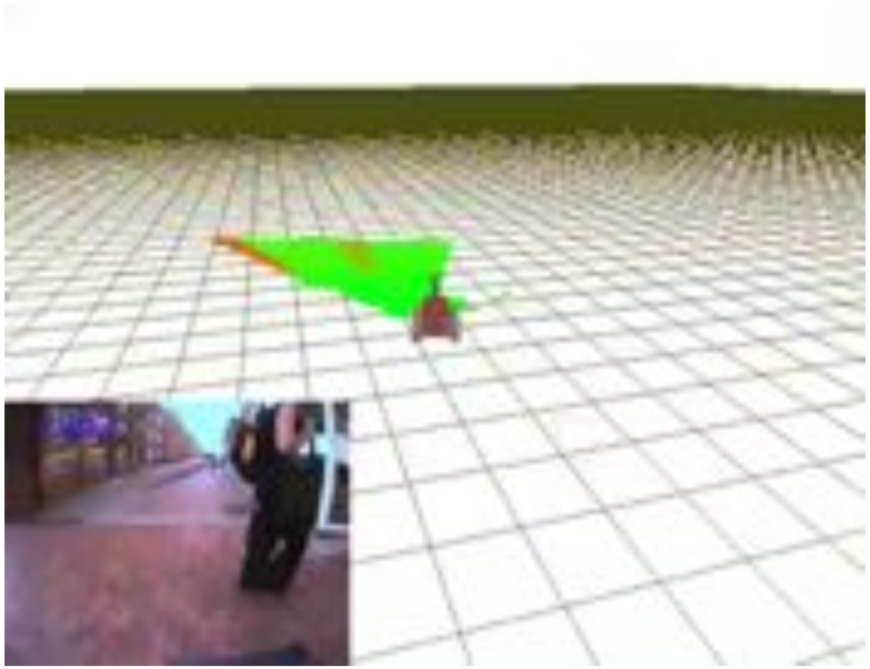
With a UAV, using a Lidar

Resampling data to obtain a *z=f(x,y)* representation on a regular Cartesian grid

[Paul Chavent @ Onera Toulouse]

Building a traversability model

With a rover, using point clouds (here stereo)
    Probabilistic labeling (Bayesian supervised learning)

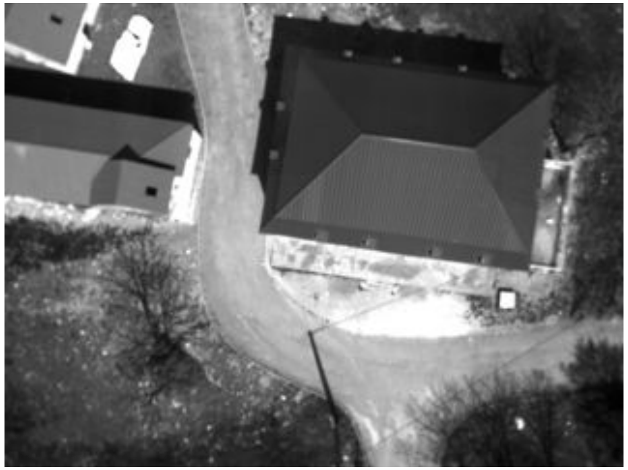


Possibility to introduce luminance / texture attributes
Much more up-to-date classification / learning processes exist

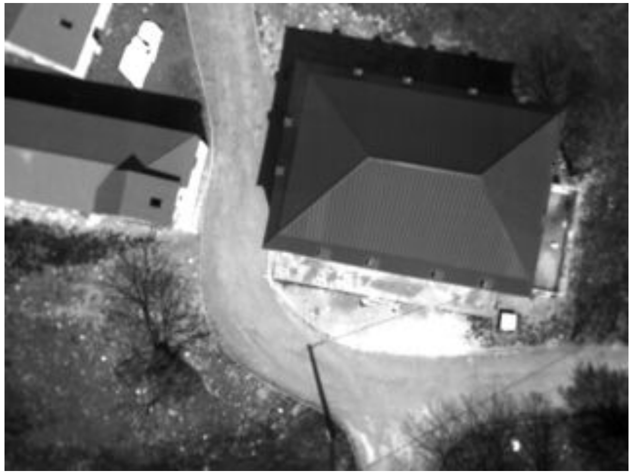
Building a traversability model

With a drone, using vision

img1



img2



Building a traversability model

With a drone, using vision

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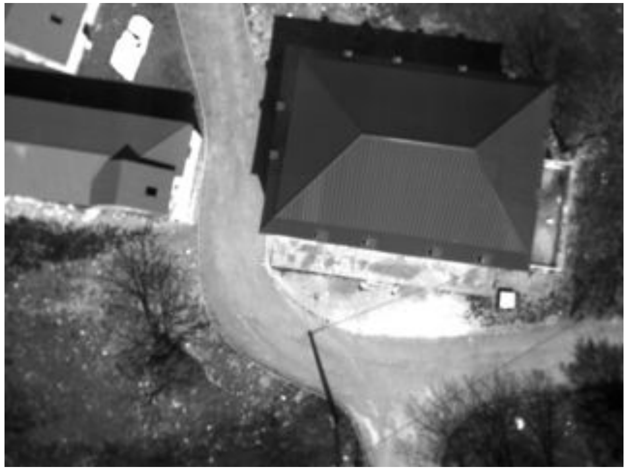

img2

Building a traversability model

With a drone, using vision

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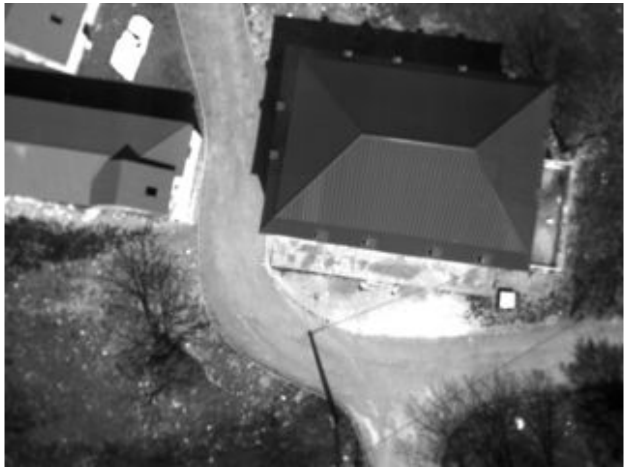

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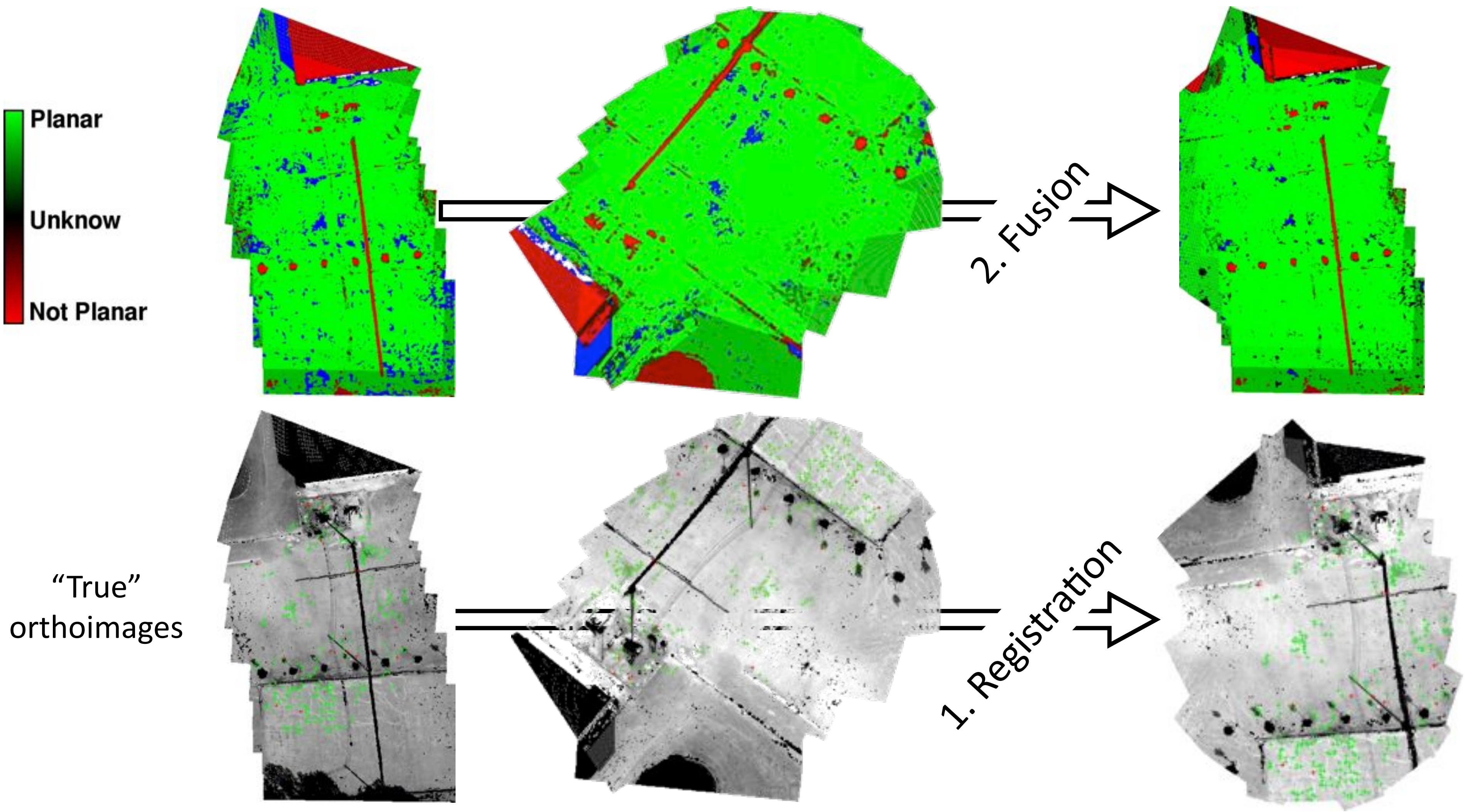
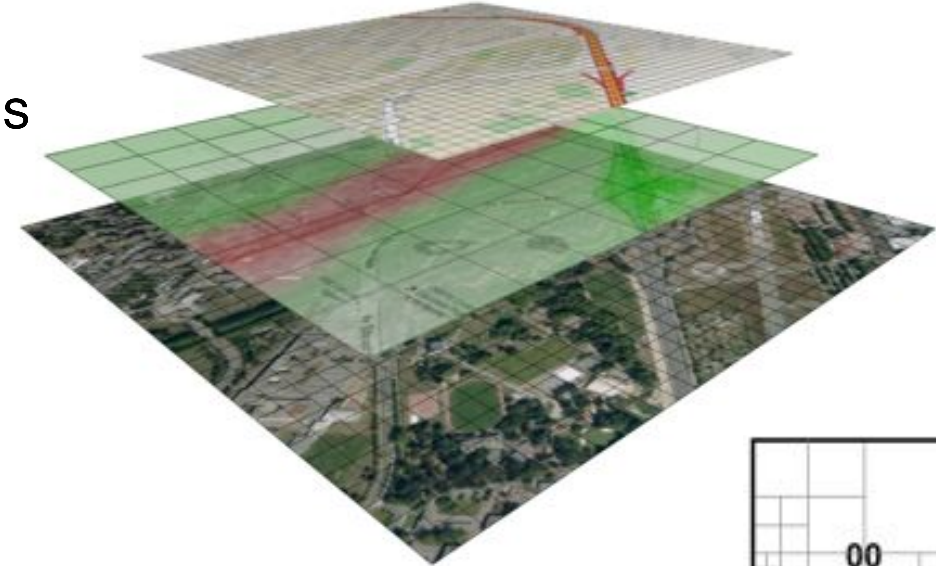
Building a traversability model

With a drone, using vision

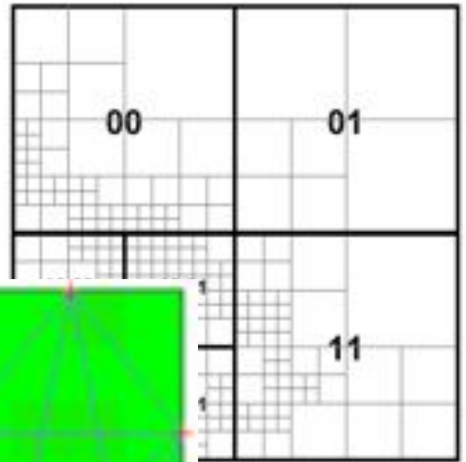


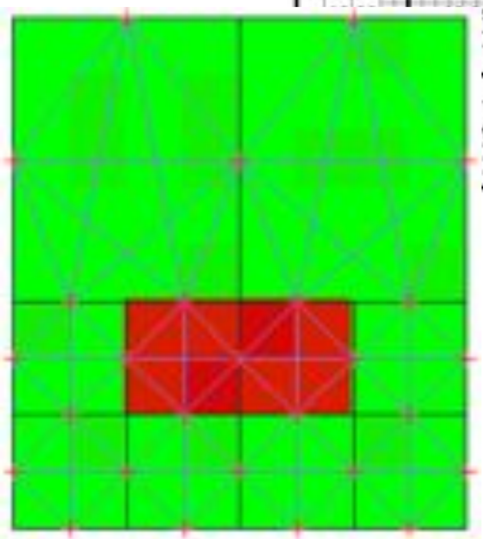
Terrain models: data structures

"Raster" models:
regular Cartesian grids



"Raster" models: hierarchical Cartesian grids

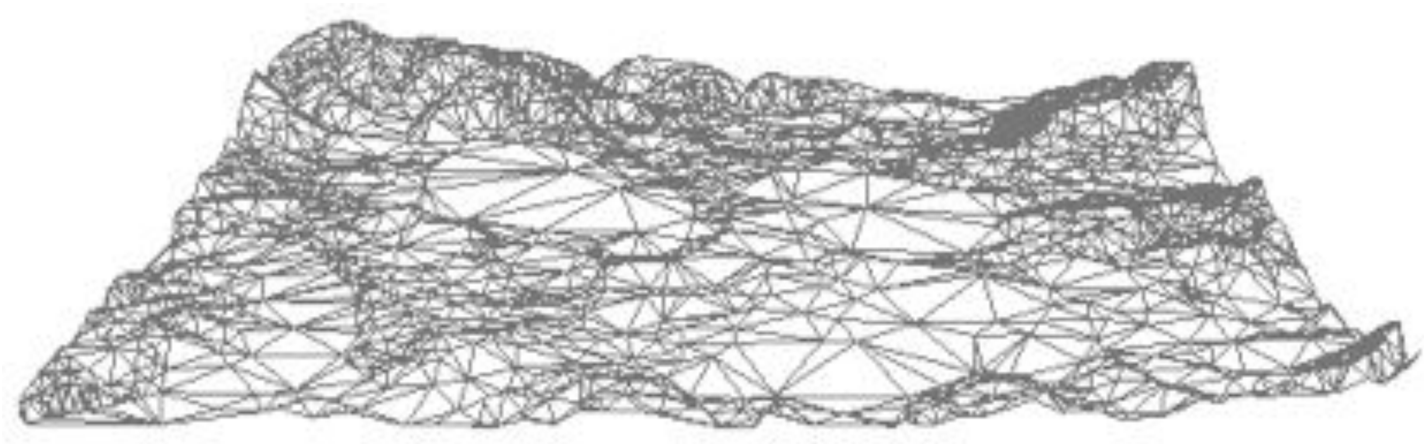




➡ Graph structures easily derived

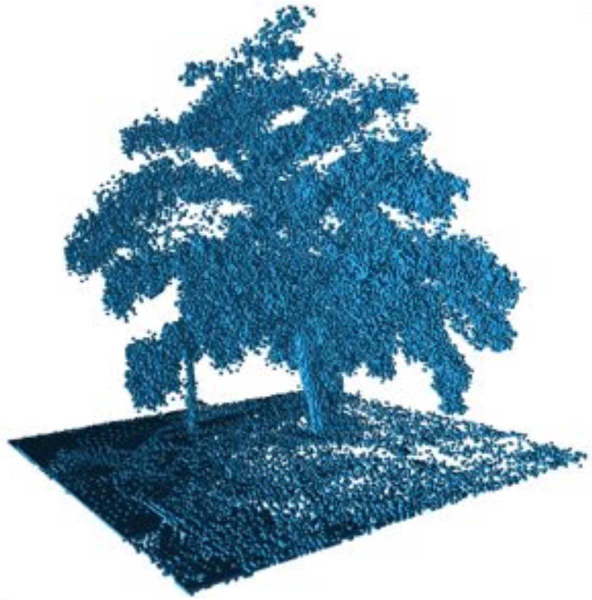
Terrain models: data structures

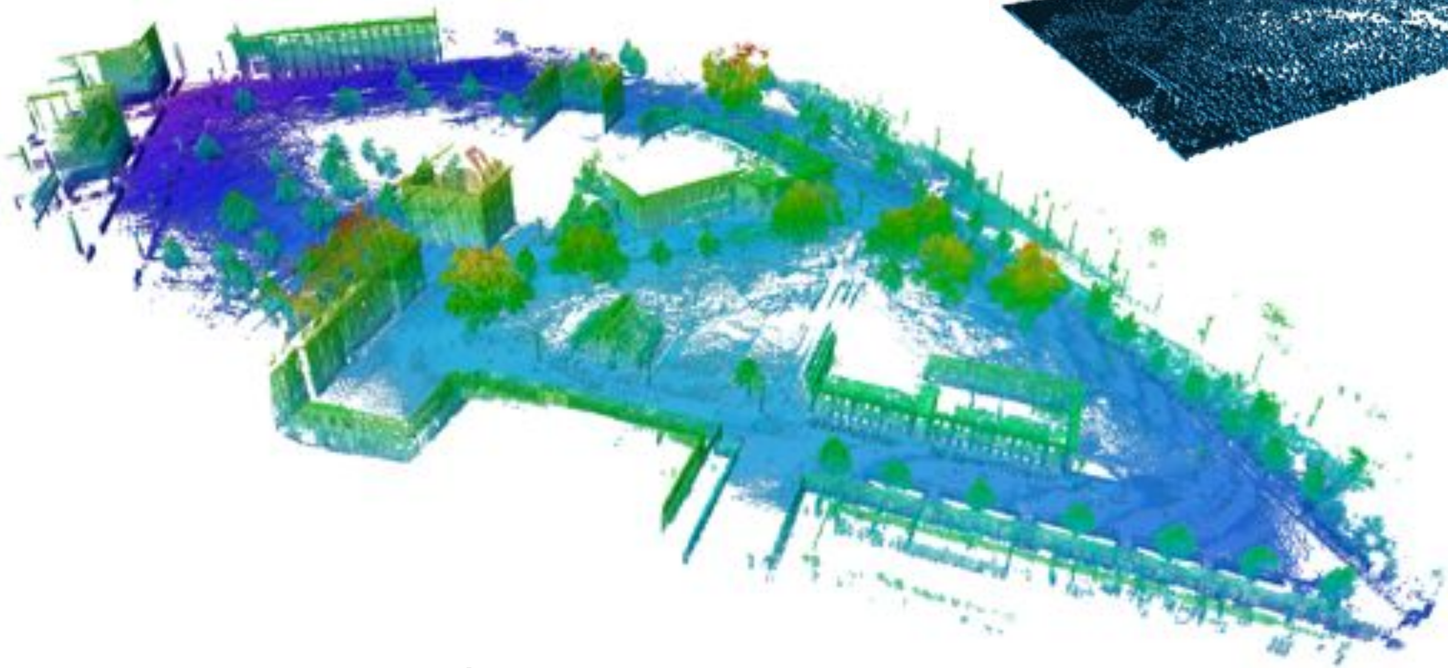
Triangular irregular meshes



Terrain models: data structures

Volumetric representations: octrees
[octomap]

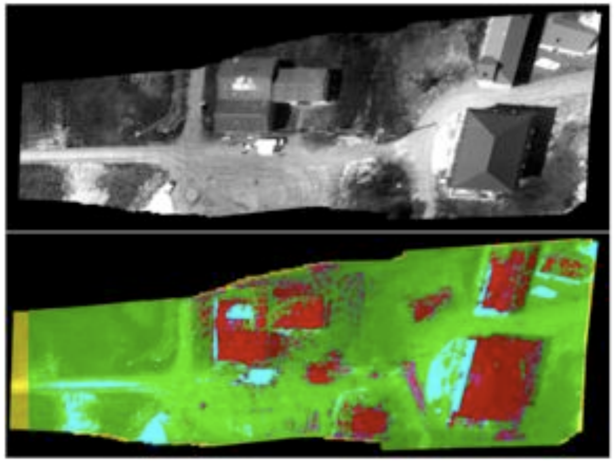


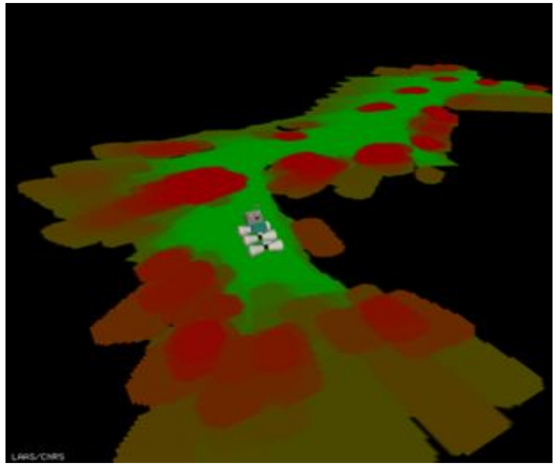


➡ Allows 3D visibility computations

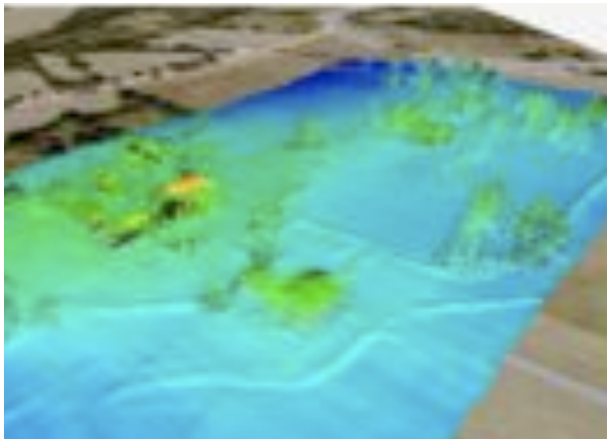
Merging air/ground models?

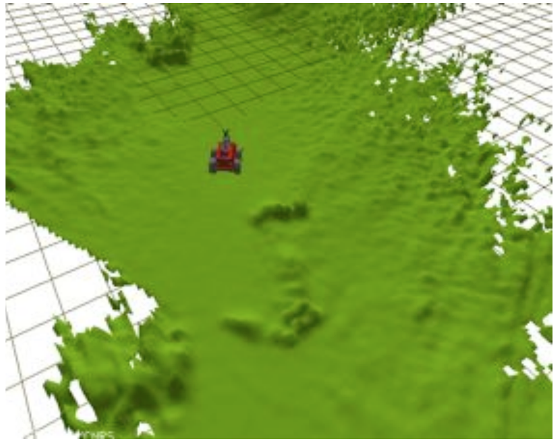
Traversability models





Digital terrain models





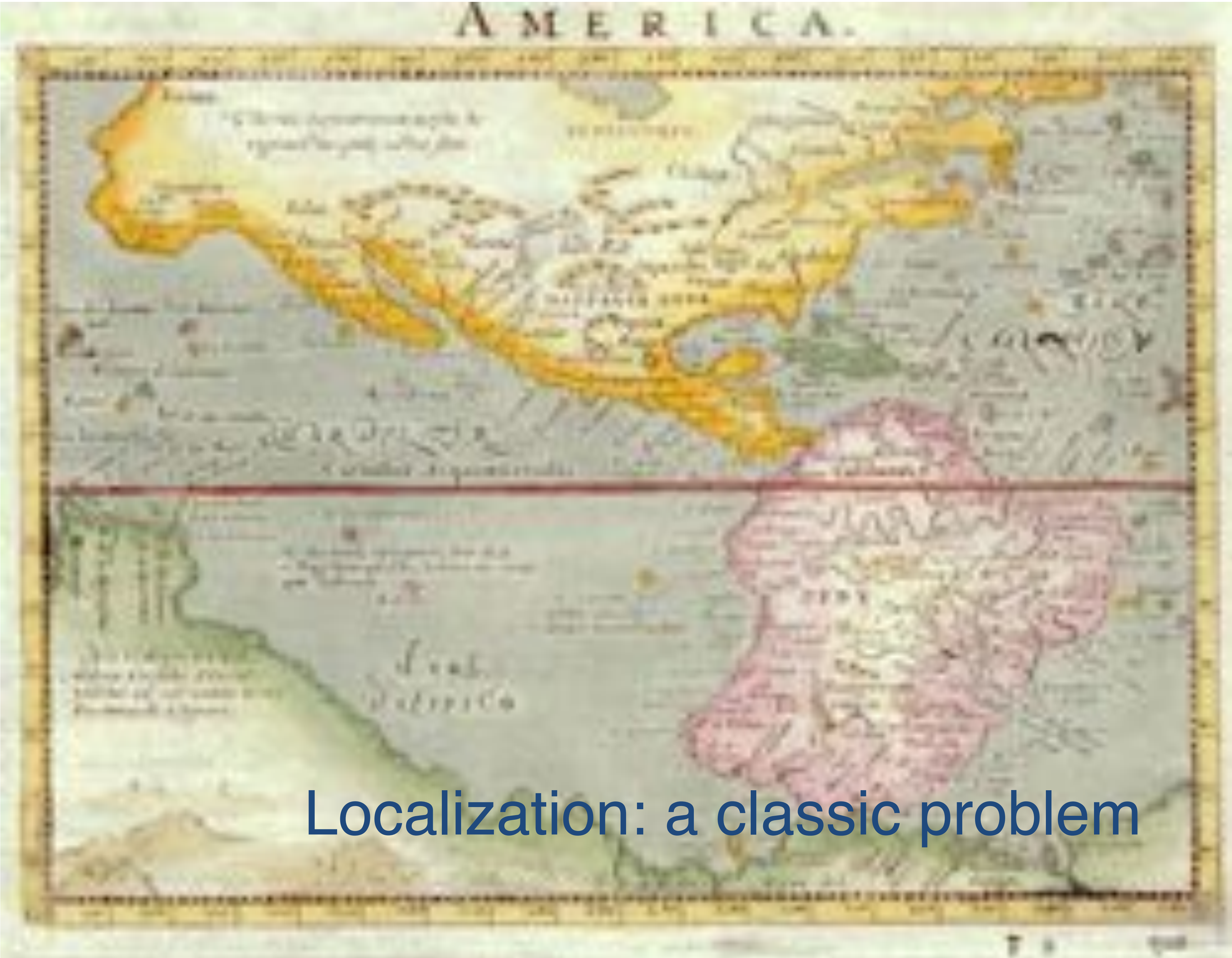
Inter-robot spatial consistency required

Terrain models: key points

1. Whatever the encoded information (terrain class, elevation, traversability, ...), it is *essential* maintain its “quality” (confidence, precision, certainty…):

    - To fuse the various sources of information
        - initial model
        - models built by other robots
        - sensor data
    - To drive the decision processes

2. Spatial consistency is crucial



Localization: a classic problem

On the importance of localization

Localization is required to:

- Ensure the spatial consistency of the built models

- Ensure the achievement of the missions, most often defined in localization tems (“`goto [goal]`”, “`explore / monitor [area]`”, …)

- Ensure the lowest level (locomotion) controls

- Ensure the proper execution of paths / trajectories

Localization solutions

Huge corpus of technological / algorithmic solutions

- Motion / accelerations sensors (dead reckoning):
  Inherently drifts over time and distances

- Absolute localization means (*e.g.* radioed beacons)
  Hardly reliable, often too coarse

➡ Develop solutions relying on the robot exteroceptive sensors

On the importance of localization

But… what localization?

Essential questions to answer:

1. With which precision ? — From *cm* to *meters*
2. In which frame ? — Absolute vs. local
3. At which frequency? — From *kHz* to “sometimes”

cm accuracy, @ > 100 *Hz*, local frame

- Ensure the lowest level (locomotion) controls
- Ensure the proper execution of paths / trajectories
- Ensure the spatial consistency of the built models

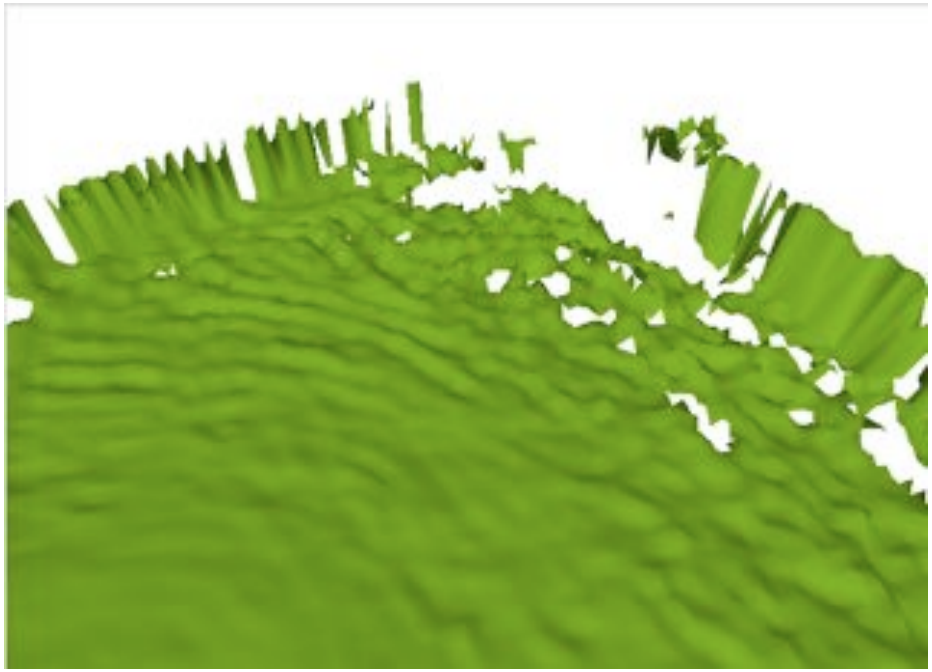
~*m* accuracy, “sometimes”, global frame

- Ensure the achievement of the missions, most often defined in localization tems (“`goto [goal]`”, “`explore / monitor [area]`”, …)

Localization precision required for a DTM

➡ DTM resolution ~ *10cm,* height precision ~ *3cm*

- Velodyne lidar provides chunks of 64 points @ 3.5 *kHz:*
  1° error on pitch yields a 17*cm* elevation error @ 10*m*

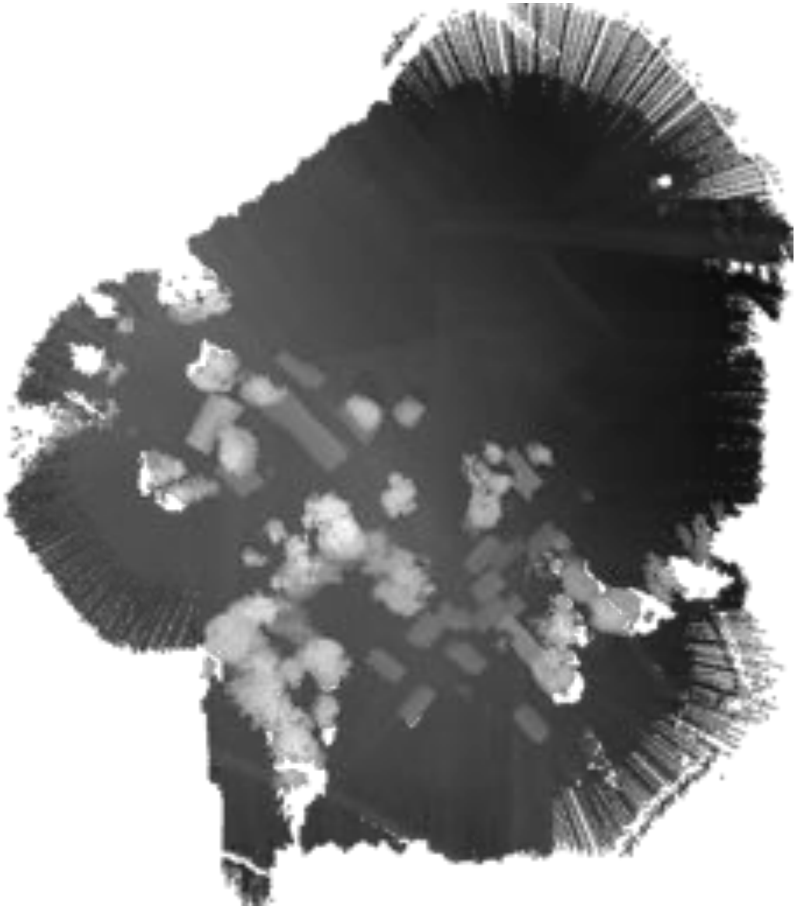


2*m/s*, GPS RTK @ 20*Hz*
+ Xsens AHRS @ 100*Hz*
+ FOG gyro @ 50*Hz*

Localization precision required for a DTM

- DTM built by an UAV with a Lidar

2*m/s*, GPS RTK @ 20*Hz*
+ INS @ x *Hz*
+ dynamic model
+ compass x *Hz*



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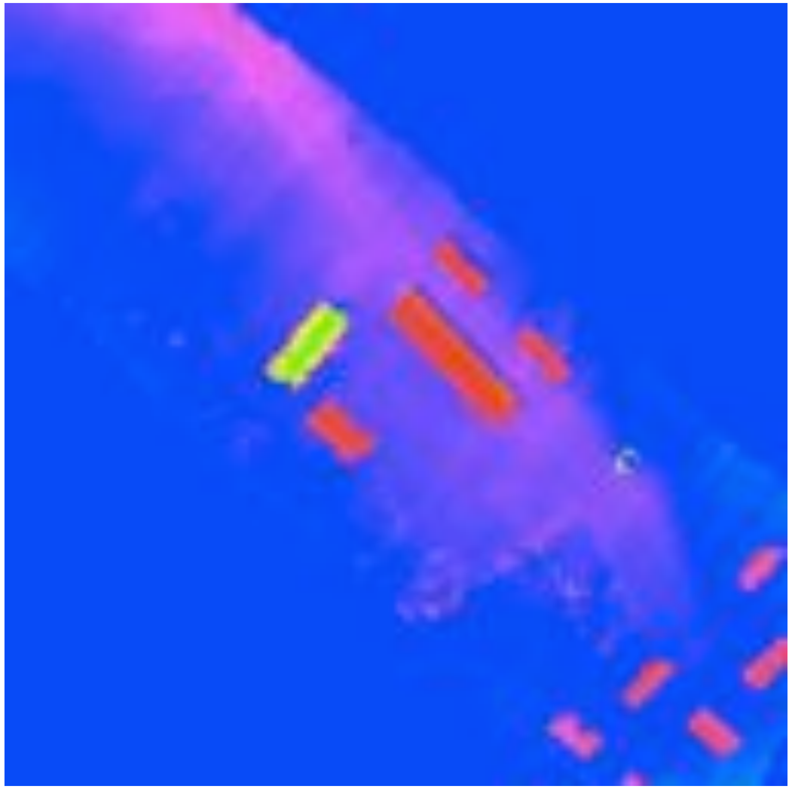
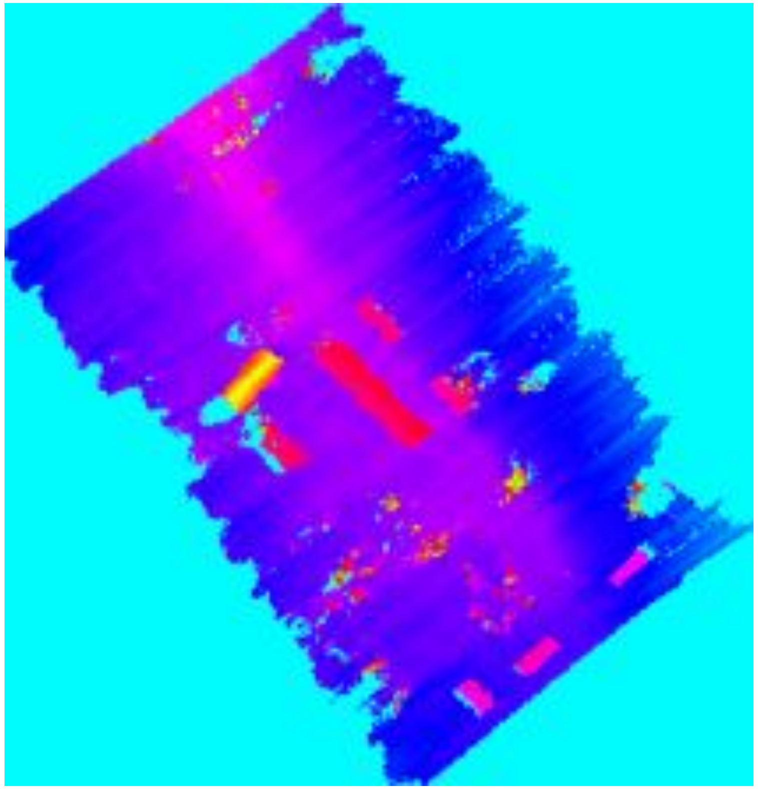
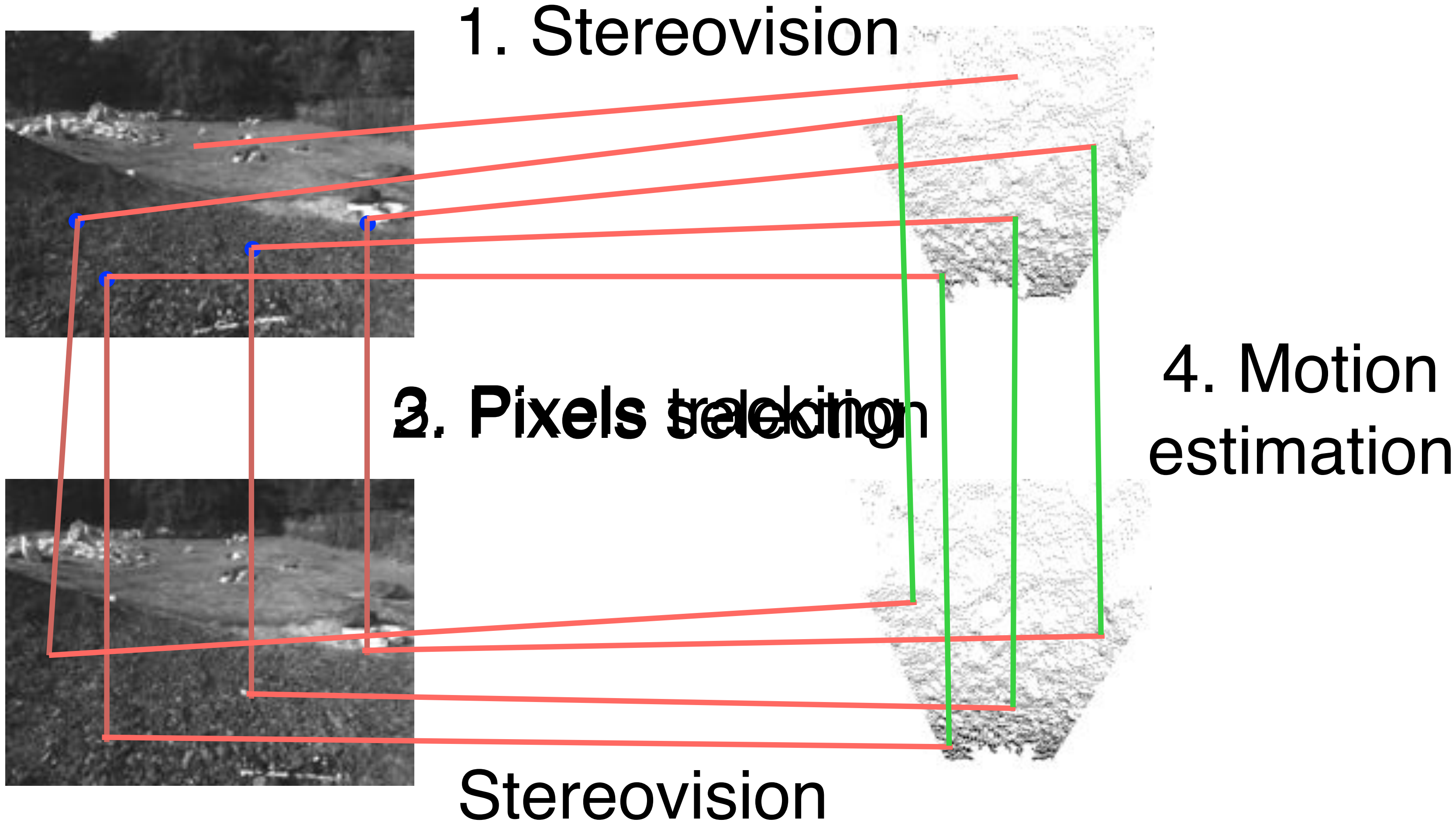


During a calm day



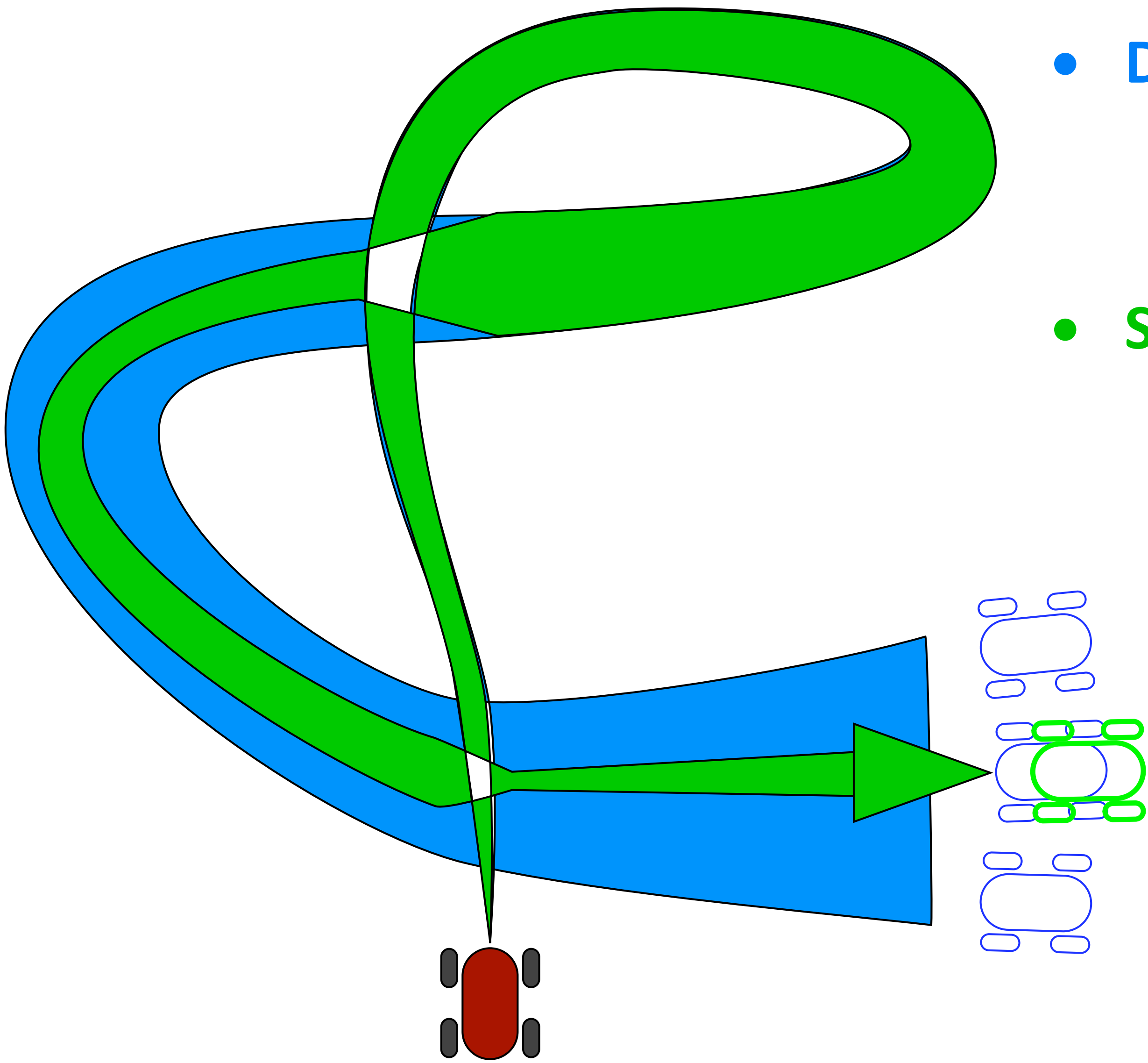
With a 10 km/h wind

Visual odometry: principle



Visual odometry on a MAV (+ 3D modelling)

“Simultaneous Localization and Mapping”



- **Dead reckoning**
  - Monotonic increase of the position uncertainty
- **SLAM**
  - “memory effect” of the mapping
  - Loop closures: position uncertainty decrase

Vision-based SLAM

Illustration: 100 Hz vision / low cost INS SLAM

Vision-based SLAM

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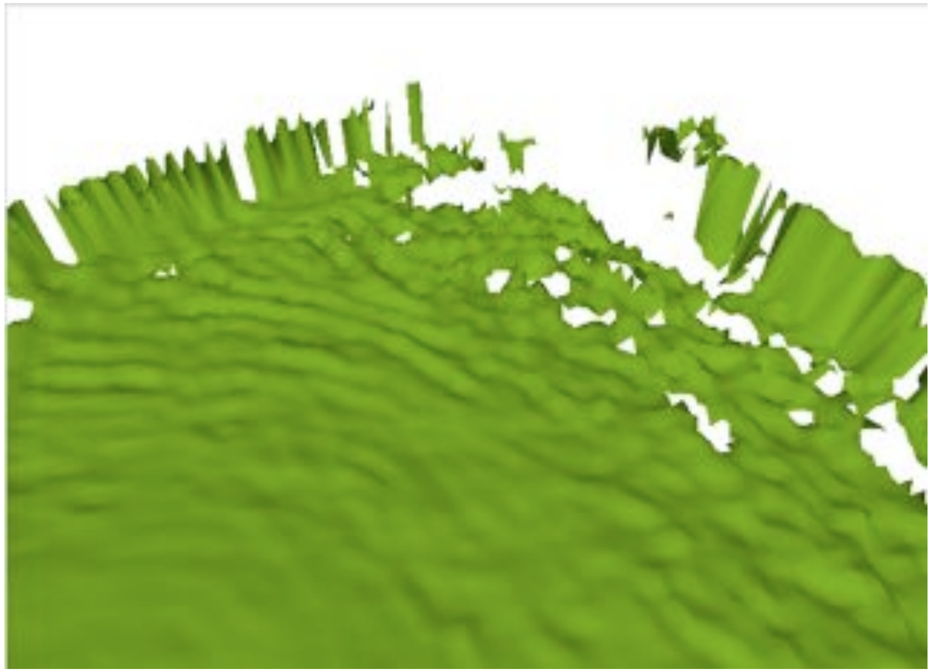
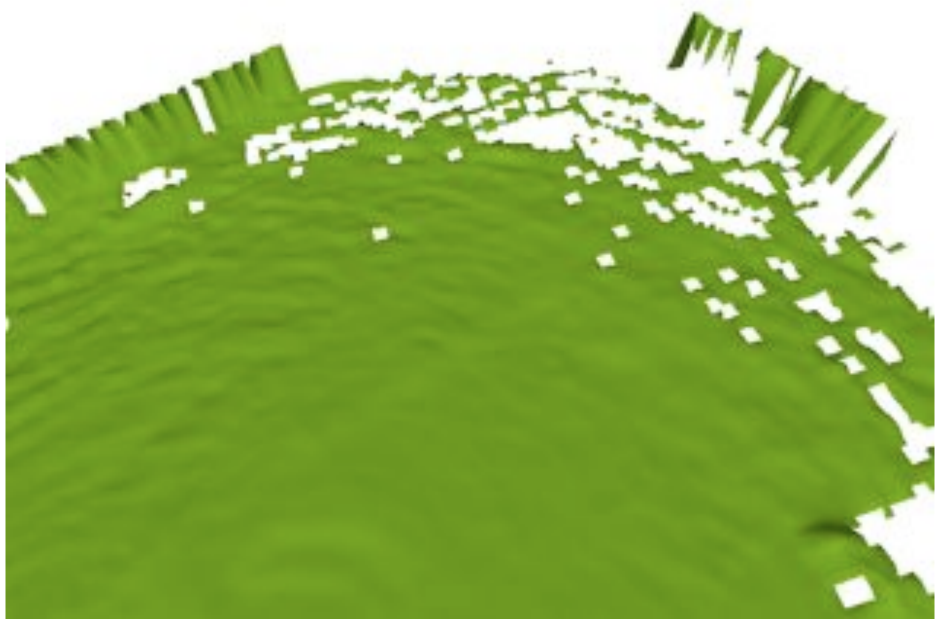


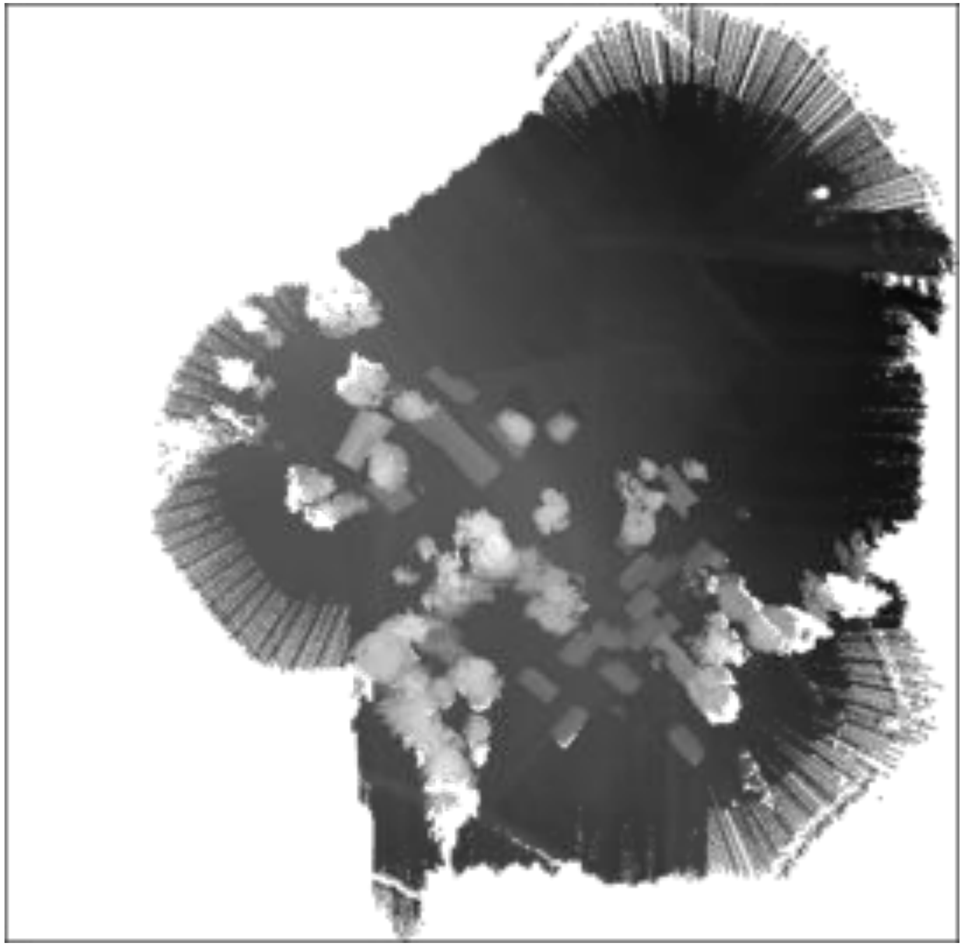
2*m/s*, GPS RTK @ 20*Hz*
+ Xsens AHRS @ 50*Hz*
+ FOG gyro @ 50*Hz*



2*m/s*, RT-SLAM @ 100*Hz*

Localization precision required for a DTM

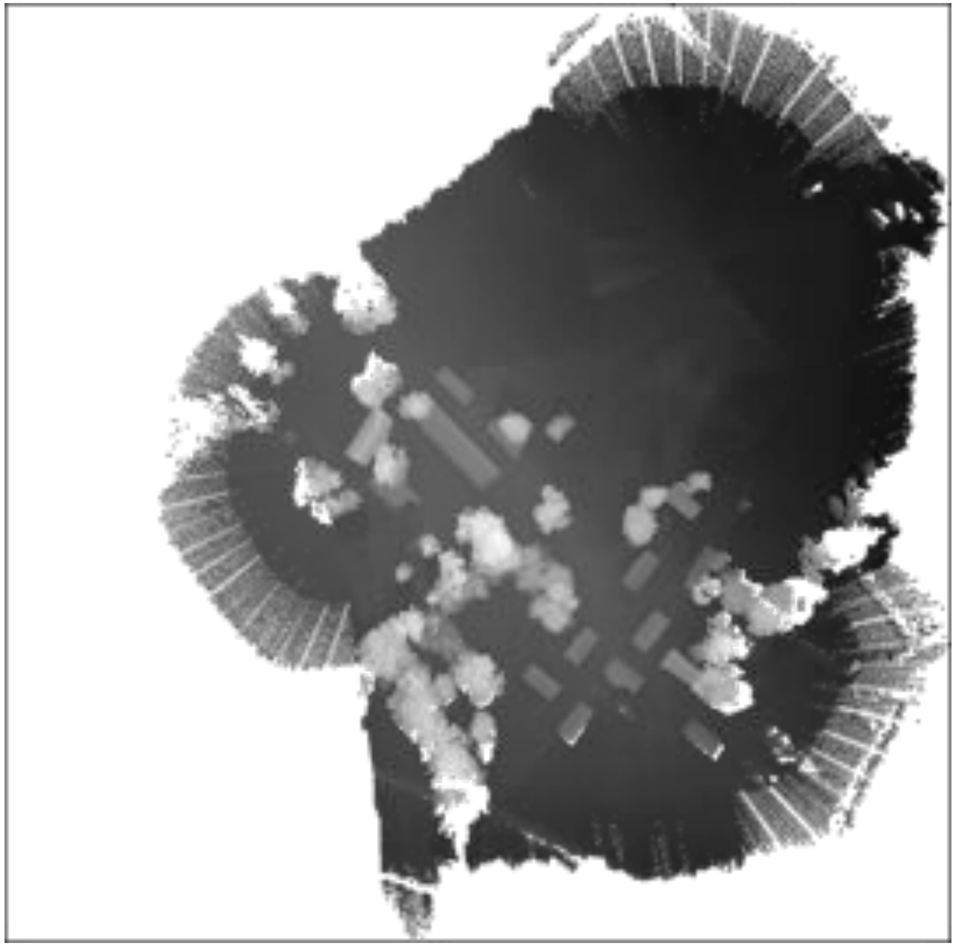
- DTM built by an UAV with a Lidar



2*m/s*, GPS RTK @ 20*Hz* + INS @ x *Hz* + *dynamic model* + compass x *Hz*

Localization precision required for a DTM

- DTM built by an UAV with a Lidar



With positions obtained after a global BA (could have been RT-SLAM)

SLAM issues

- SLAM processes complexity grows with the number of landmarks

➡ The map size can't scale up

- The convergence of Kalman filter based solutions can't be guaranteed

➡ The map size can't scale up, loop closures may lead inconsistencies

Multi-map hierarchical SLAM

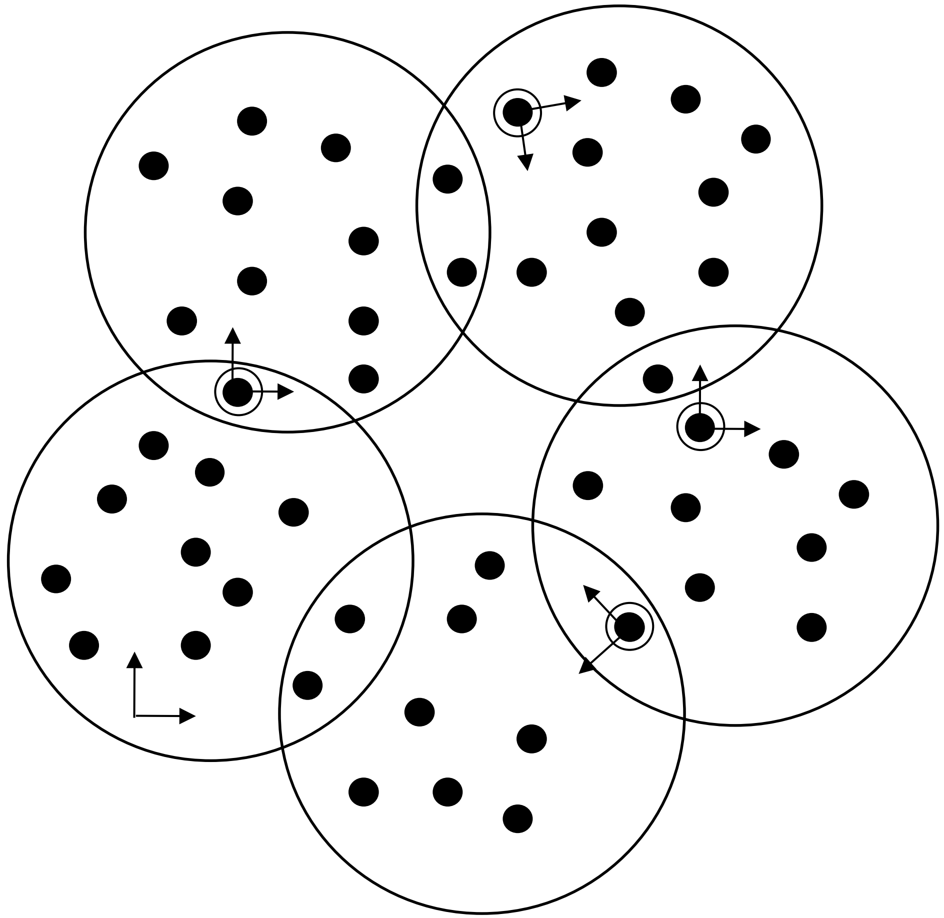
Hierarchical SLAM [Tardos-2005], a graph of "submaps":

Local maps (EKF) of current vehicle pose and landmarks pose (nodes)

Global map of relative transformations (edges)

Local maps:

- Fully correlated maps (robot and landmark states)
- No information shared between local maps
- Each map is initialized with no uncertainty



Multi-map hierarchical SLAM

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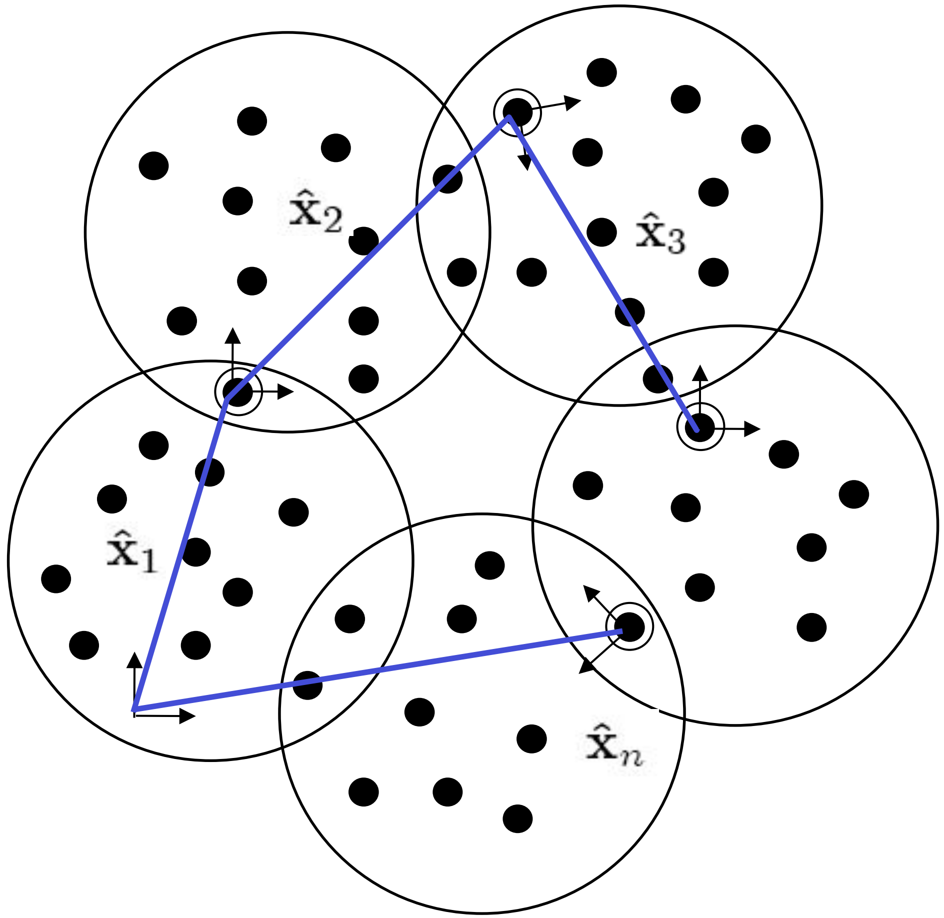
Global graph of maps:

- Robot’s pose
- The state is the relative transformation between local maps
- Block diagonal covariance before loop closure



Multi-map hierarchical SLAM

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- Local maps (EKF) of current vehicle pose and landmarks pose (nodes)
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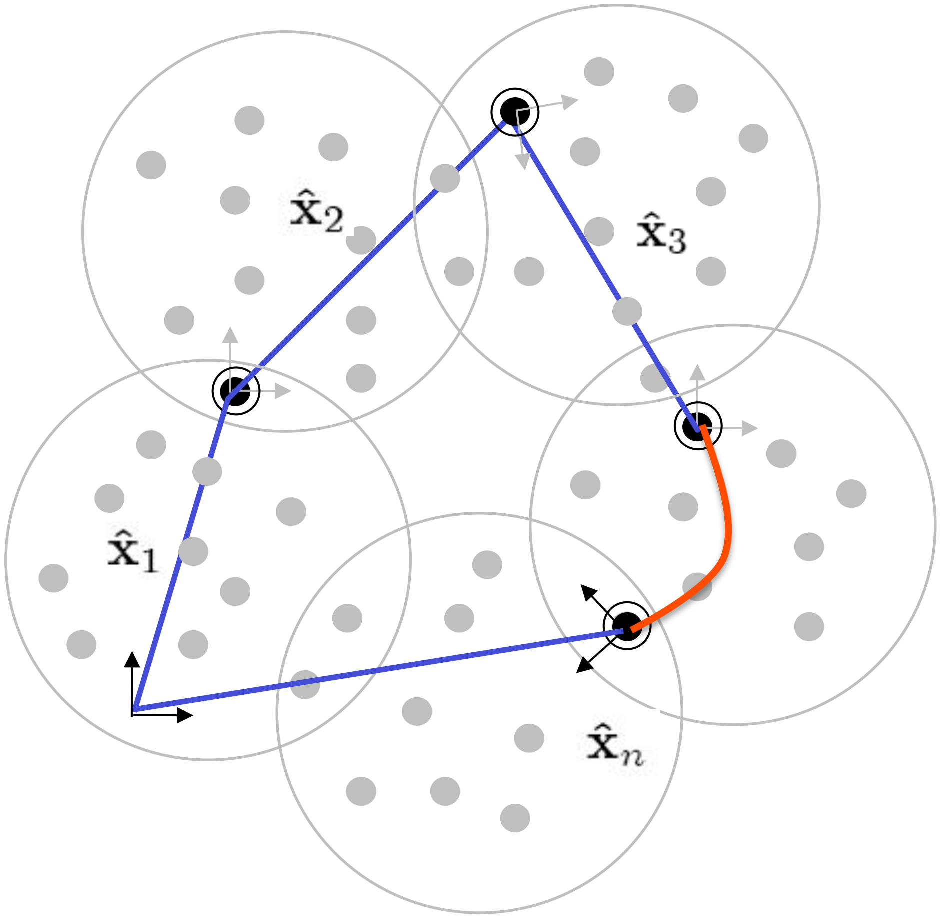
Loop closures in the global graph:

Loop constraint

$$\mathbf{h}(\mathbf{x}) = \hat{\mathbf{x}}_1 \oplus \hat{\mathbf{x}}_2 \cdots \oplus \hat{\mathbf{x}}_{n-1} \oplus \hat{\mathbf{x}}_n = \mathbf{0}$$

Minimisation subject to the loop constraint

$$\min_{\mathbf{x}} f(\mathbf{x}) = \min_{\mathbf{x}} \frac{1}{2}(\mathbf{x} - \hat{\mathbf{x}}_u)^T \mathbf{P}_u^{-1} (\mathbf{x} - \hat{\mathbf{x}}_u)$$
$$\mathbf{h}(\mathbf{x}) = \mathbf{0}$$



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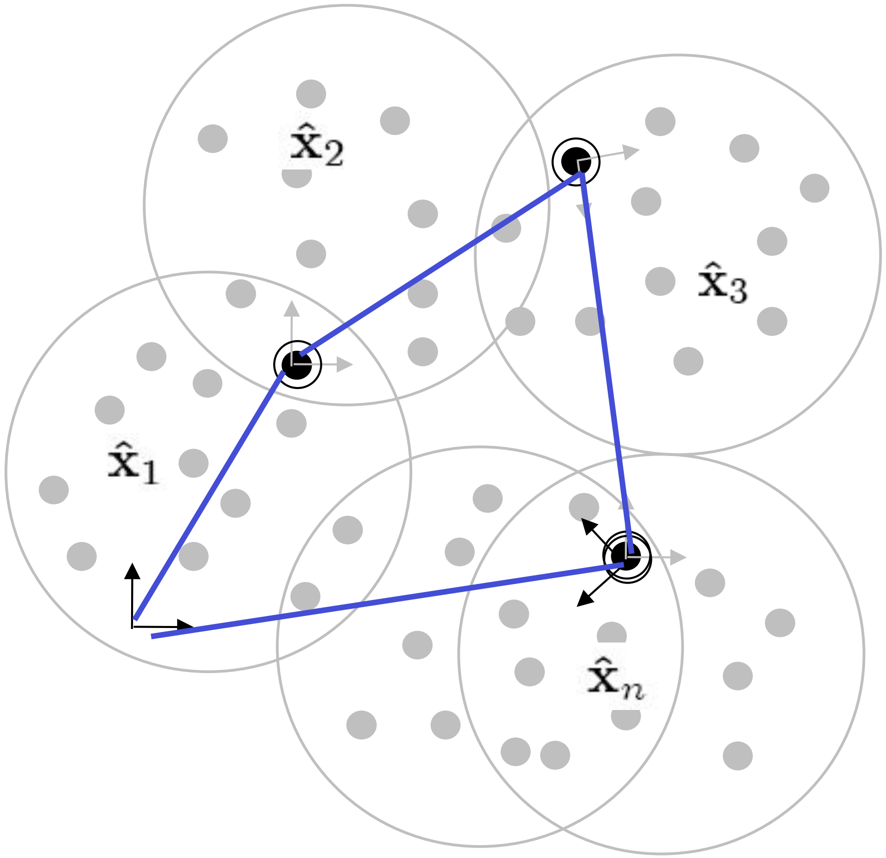
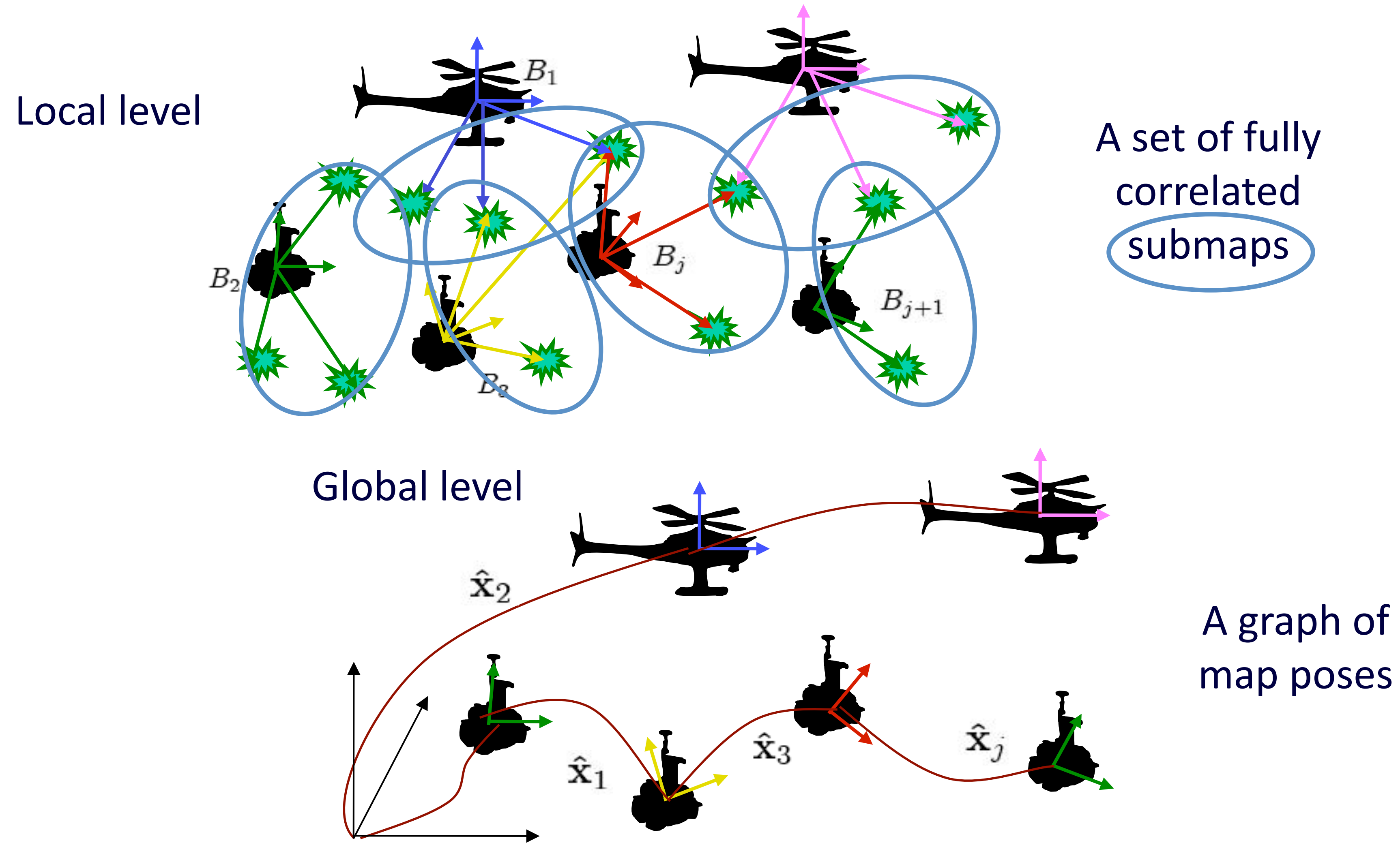


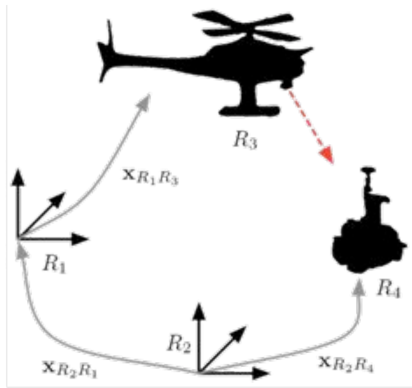
A distributed multi-robots multi-map approach

- Straightforward extension to hierarchical SLAM

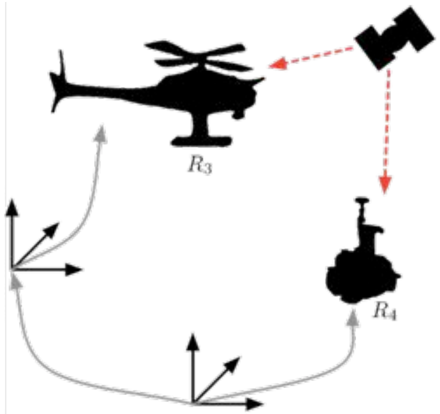


A distributed multi-robots multi-map approach

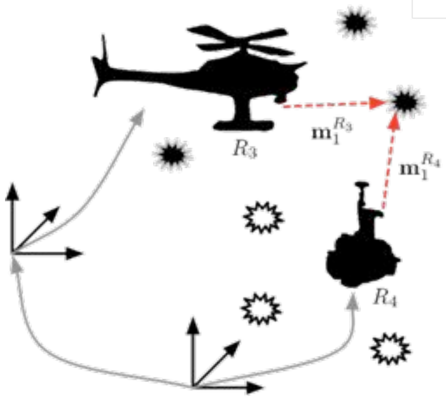
➡ Various loop-closing events



"Rendez-vous": inter-robot pose estimation



Absolute localization (GPS fix / localization wrt. an initial map)



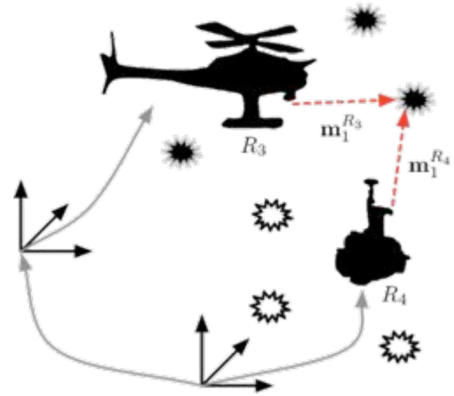
Inter-robot landmark (or map) matches

Detecting loop closures between air/ground robots

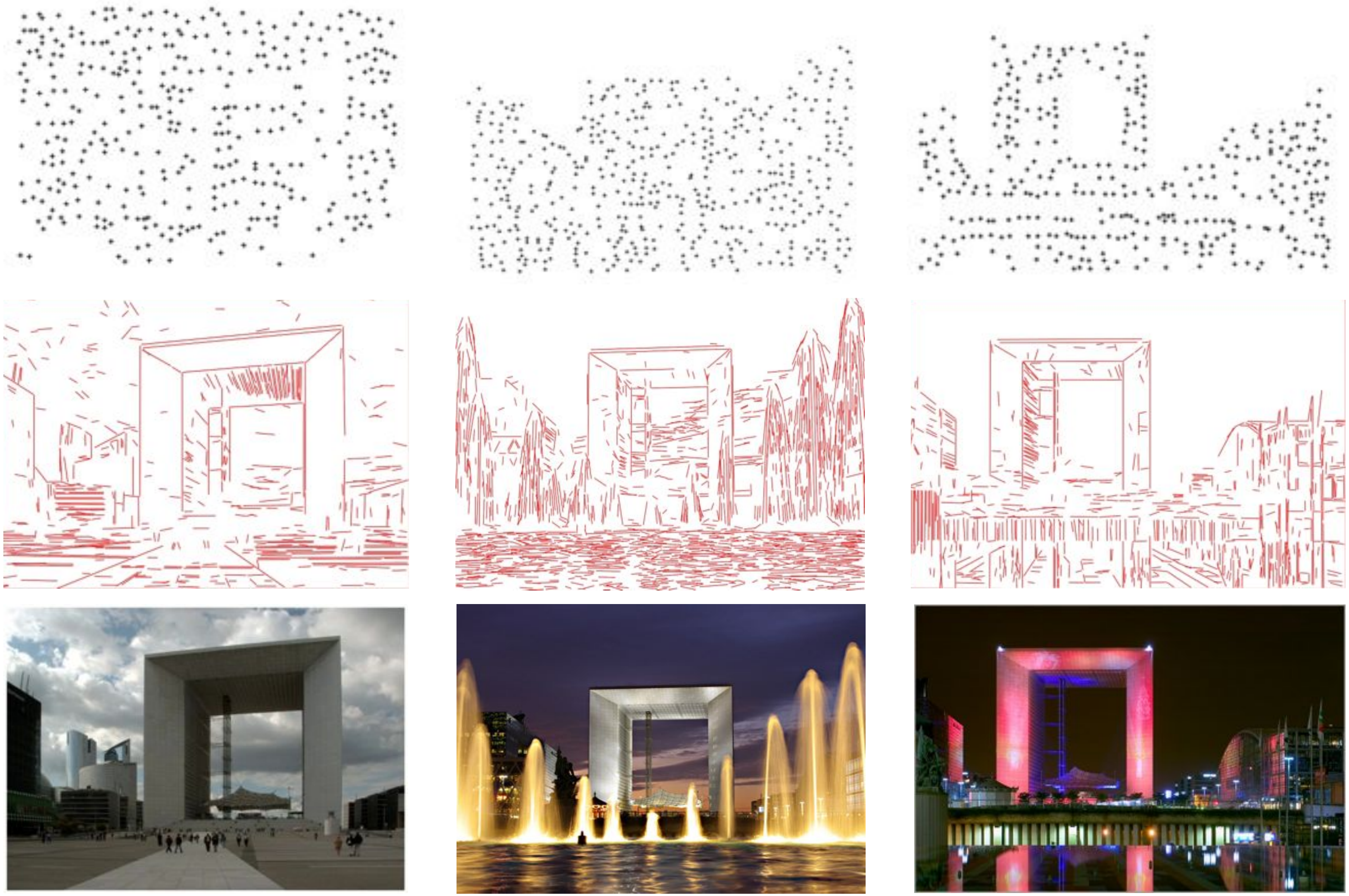
Visual point landmarks can't be exploited

Need to focus on the M of SLAM

➡ <u>Geometry</u> is the key



Points vs. lines in vision

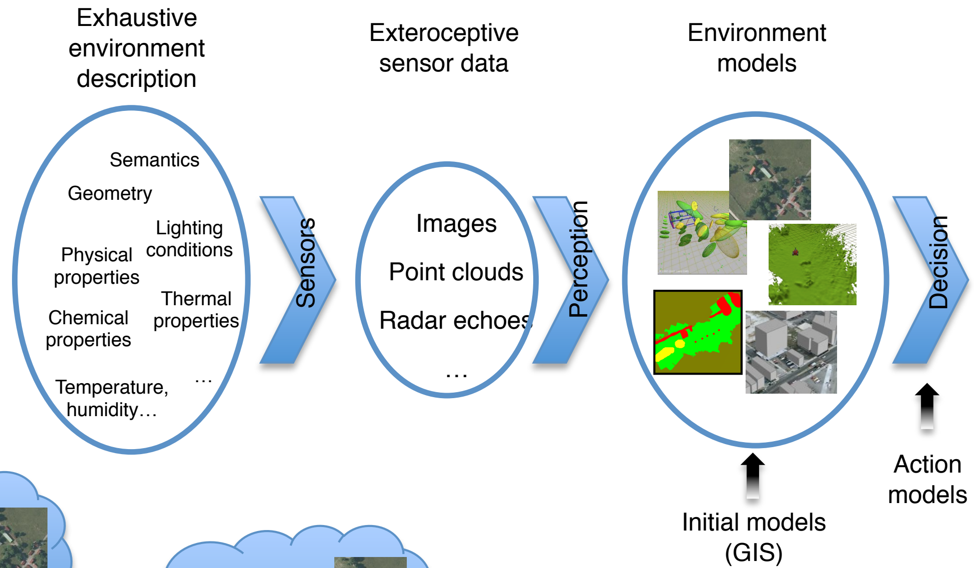


Preliminary multi-robot SLAM results

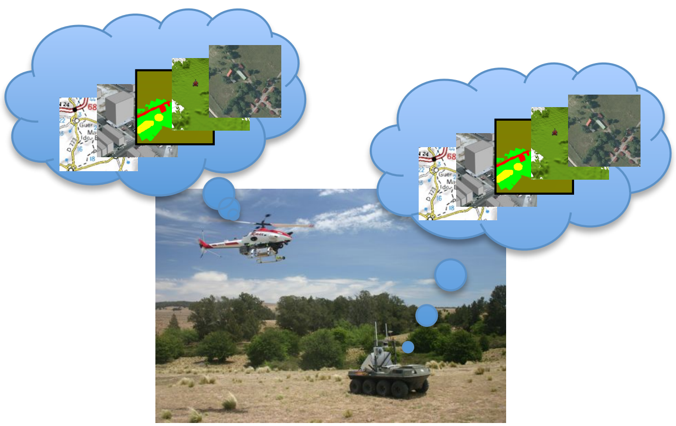
Research perspectives on envt. models

Focus on geometric (3d, vectorized) representations

Integrate existing data (GIS)



Distributed models Management



Humans in the loop: information sharing (spatial ontologies ?)

Outline

Notion of Autonomy

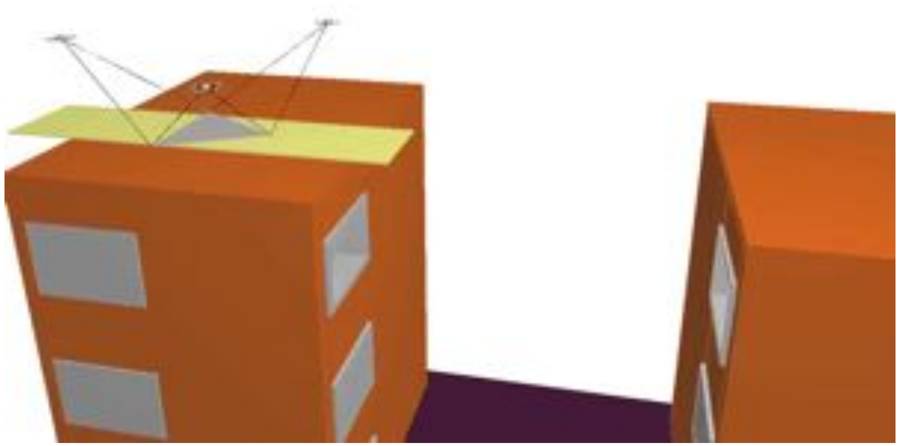
Multiple UAVs in the sky
- Monitoring a set of locations
- Fly a flock of drones amidst threats

Multiple UAV/UGV systems
- Illustrations: need for environments models
- Illustration of environment model building processes
- Importance of localization

Current projects

The ARCAS project

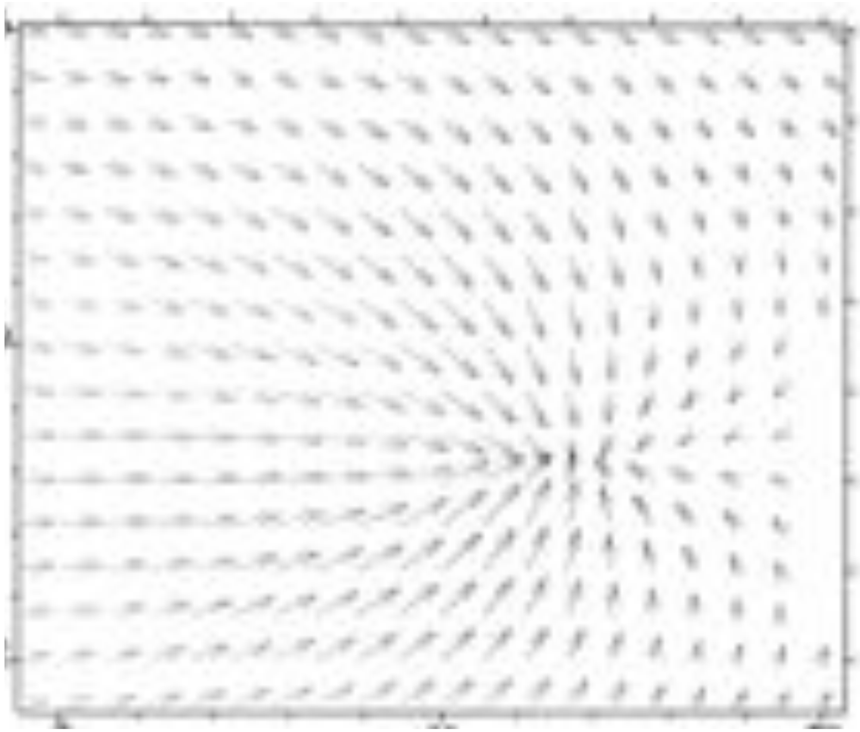
www.arcas-project.eu/ : “development and experimental validation of cooperative UAV systems for assembly and structure construction”



The SkyScanner project

Adaptive synchronous sampling of clouds with a fleet of UAVs

(energy harvesting)



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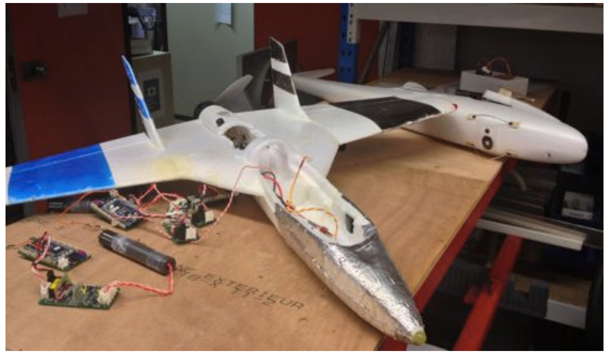

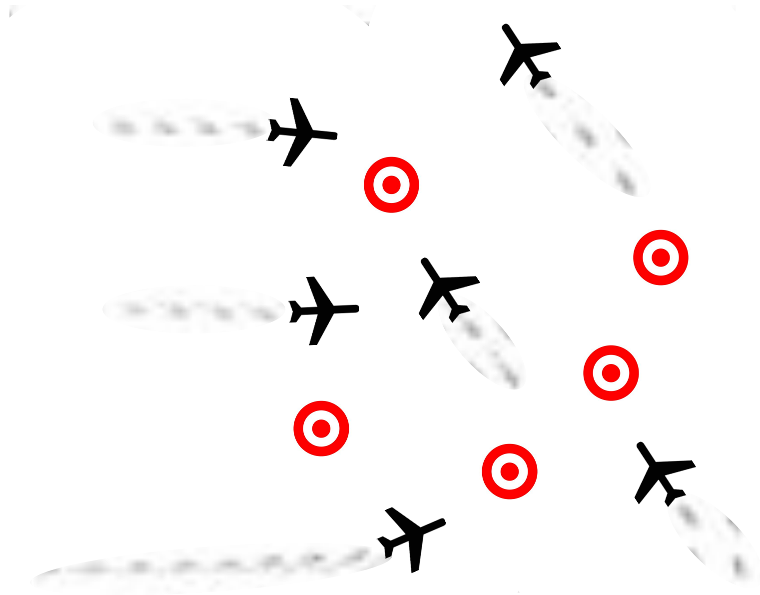

At each At time t

1. Collect infos. where ?

2. Who flies where ?

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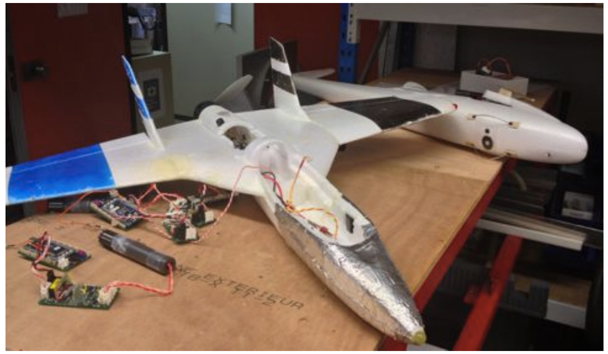

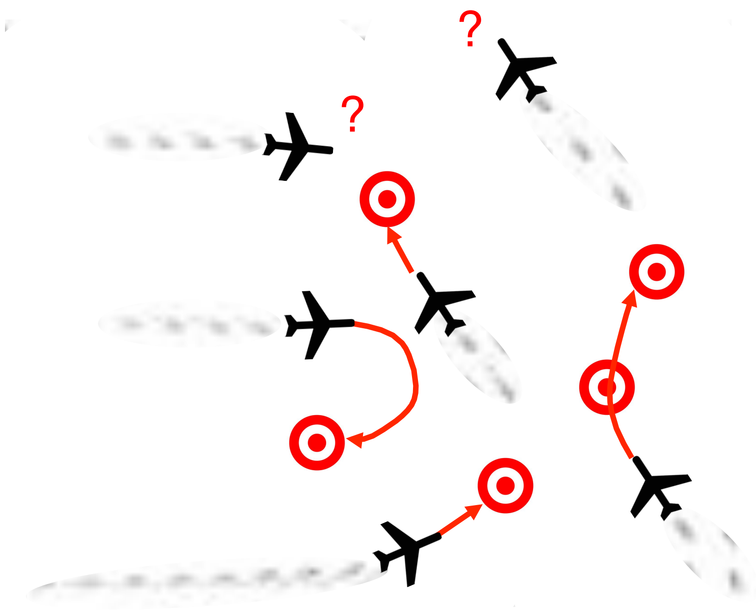

À un instant t

1. Collect infos. where ?

2. Who flies where ?

Take home messages

• Autonomy calls for specific decisional processes

• Good representations are the foundations of good decisions, and hence of good cooperations

• A *variety* of representations is required

• Geometry is certainly the most important information to represent (but not only)

• Maintaining the quality of information is essential