



Cognitive and Collaborative sUAS Swarms in Urban Environments

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Introduction – sUAS Application Examples

Commercial:

- Delivery
- Surveying and Mapping
- Forestry Agriculture
- Imaging News and Media Support

First Response:

- Search and Rescue
- Law Enforcement
- Forest Fire Monitoring
- Disaster Relief

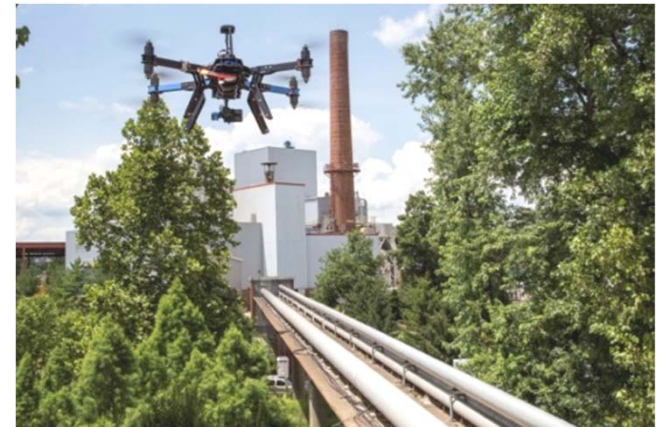
Scientific:

- Environmental Monitoring
- Hyper spectral Imaging
- Archaeology
- Natural Resource Exploration

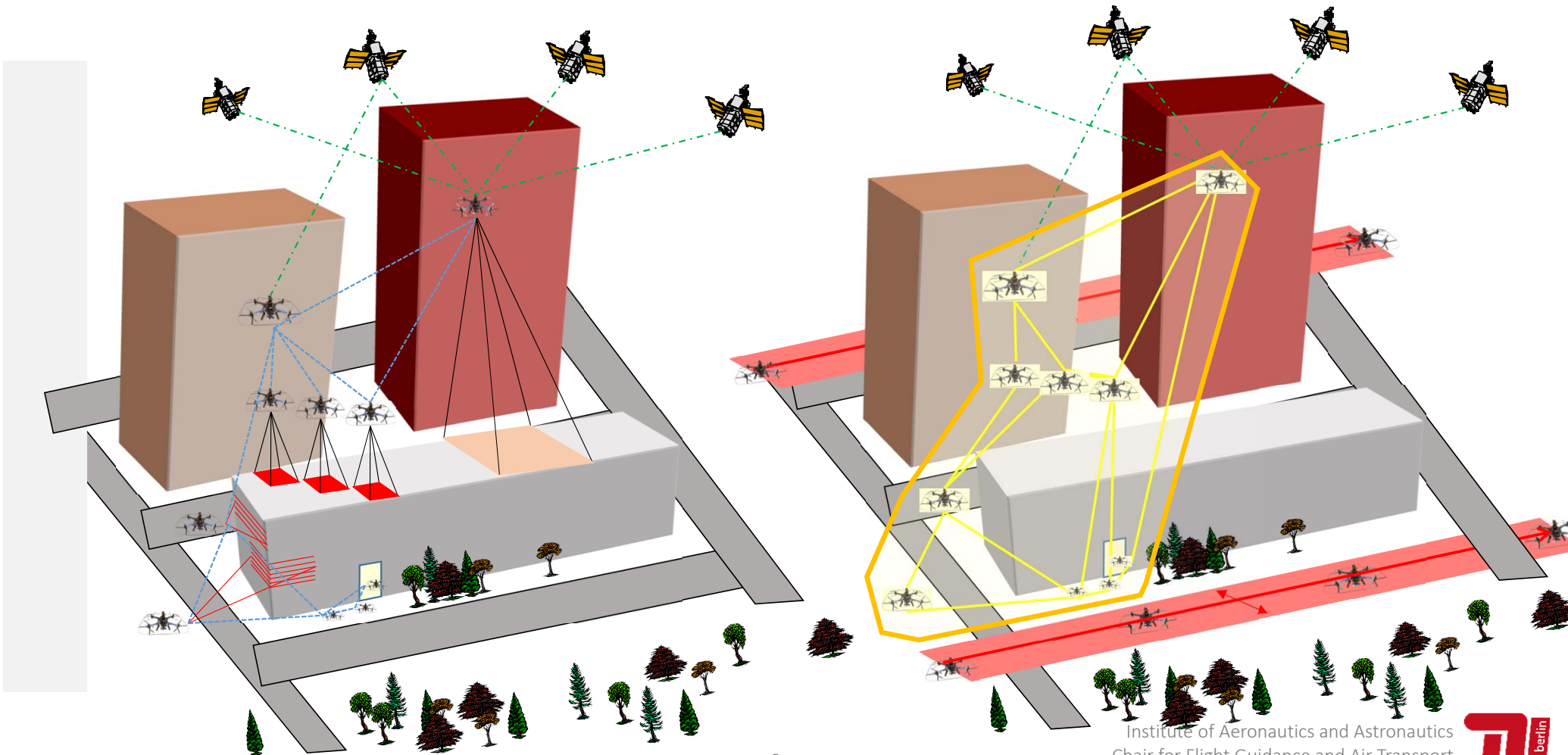
Security:

- Border Patrol
- Surveillance
- Training
- Military

Many of these applications can be performed with a “**fleet**” or “**swarm**” of cooperative UAS



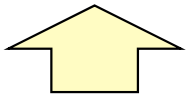
Perception, State Estimation and Protection



Application of Swarms

What do we want to achieve with the group sUAS (swarm)?

- Mission
- Address an economic need
- While gaining a public acceptance
- And addressing sustainability



Multiple smaller UA platforms:
reduced complexity and weight, increased reliability, faster mission execution

What do we need to know for this? (knowledge)

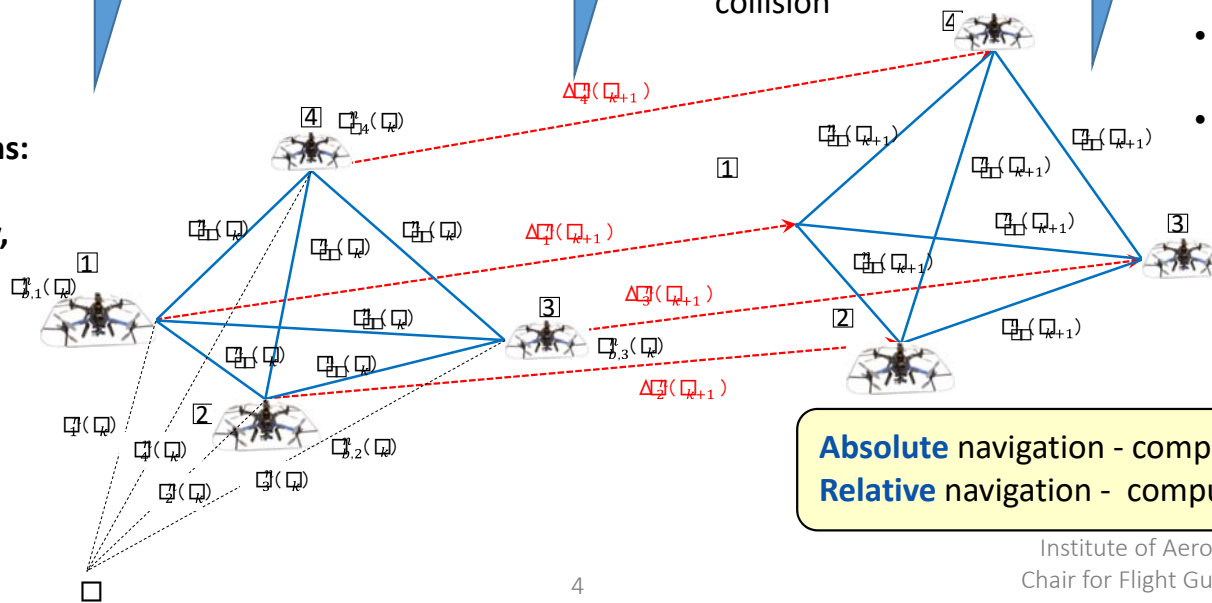
- Absolute position
- Relative position
- Separation
- External conditions
- Etc.

How good does this knowledge need to be to be acceptable? (performance requirements)

- Accuracy
- Integrity
- Availability
- Continuity
- Chance of a collision

How do we obtain this knowledge? (perception and cognition)

- Obtain measurements from sensors
- Process this sensor information
- Estimate required knowledge
- Assess if required performance is met.
- Look for alternatives



Application of Swarms

Challenging environments

What do we want to achieve with the group sUAS (swarm)?

- Mission
- Address an economic need
- While gaining a public acceptance
- And addressing sustainability

What do we need to know for this? (knowledge)

- Absolute position
- Relative position
- Separation
- External conditions
- Etc.

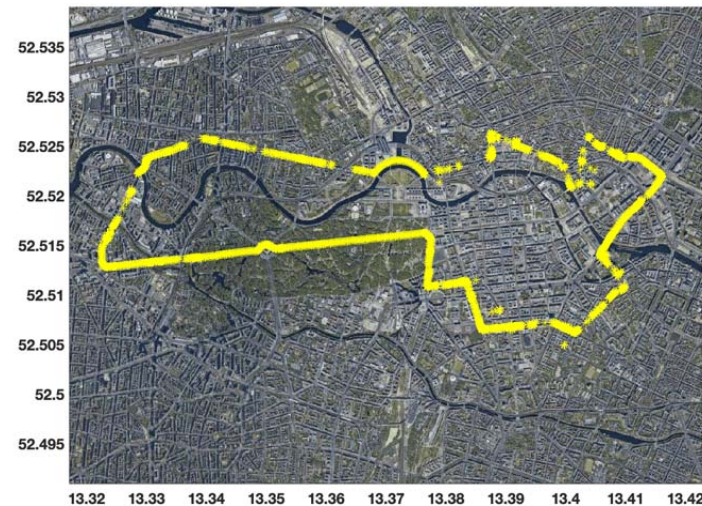
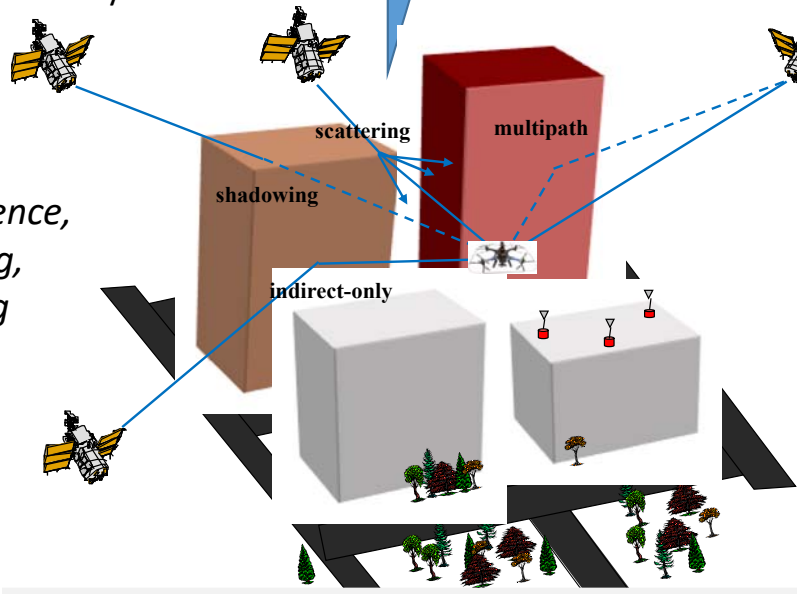
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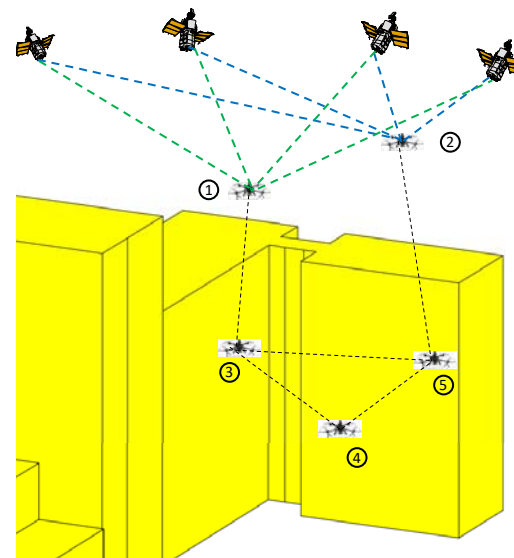
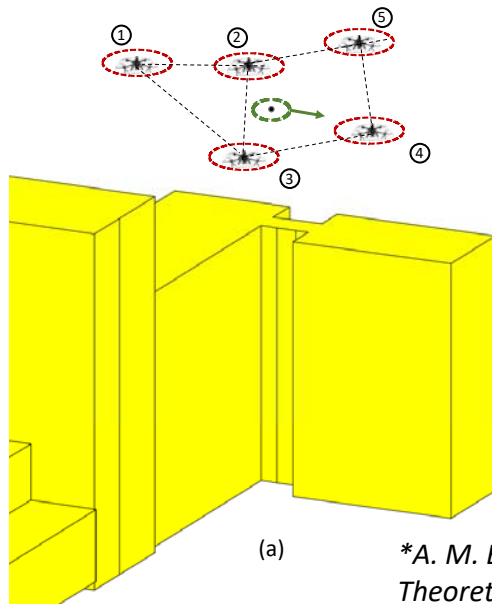
- Obtain measurements from sensors
- Process this sensor information
- Estimate required knowledge

And:
Interference,
Jamming,
Spoofing



Swarm Navigation – Learning from Nature

- **many wrongs**: improvement of the navigation performance by averaging or filtering the navigation estimates of the individual members.
- **leadership**: some swarm members have better knowledge of their navigation solution and use that knowledge to help the remaining members meet their navigation performance requirements

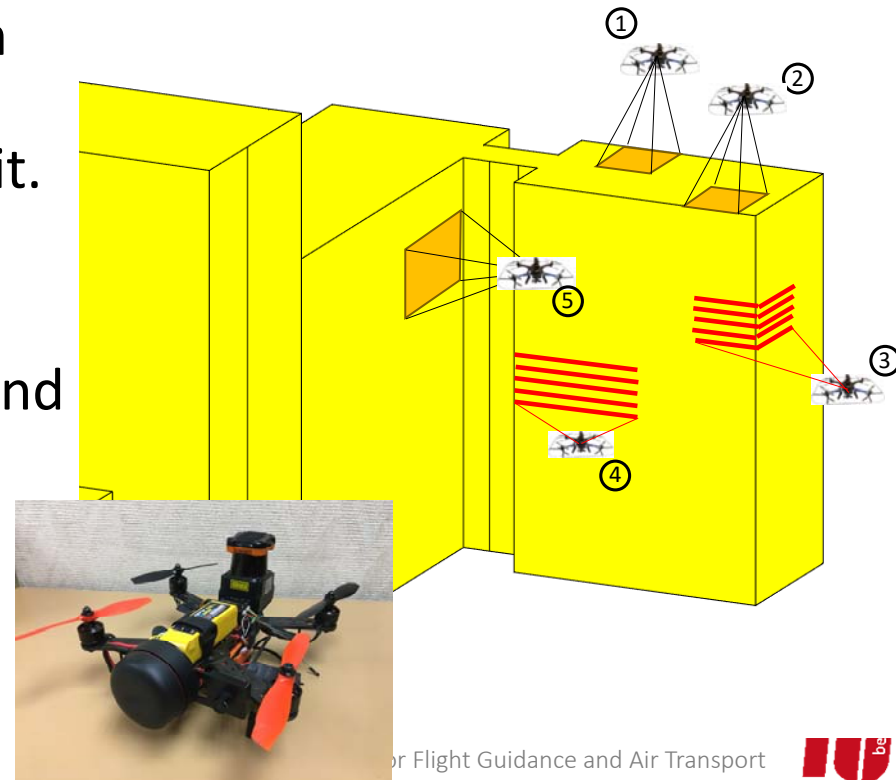


(a)

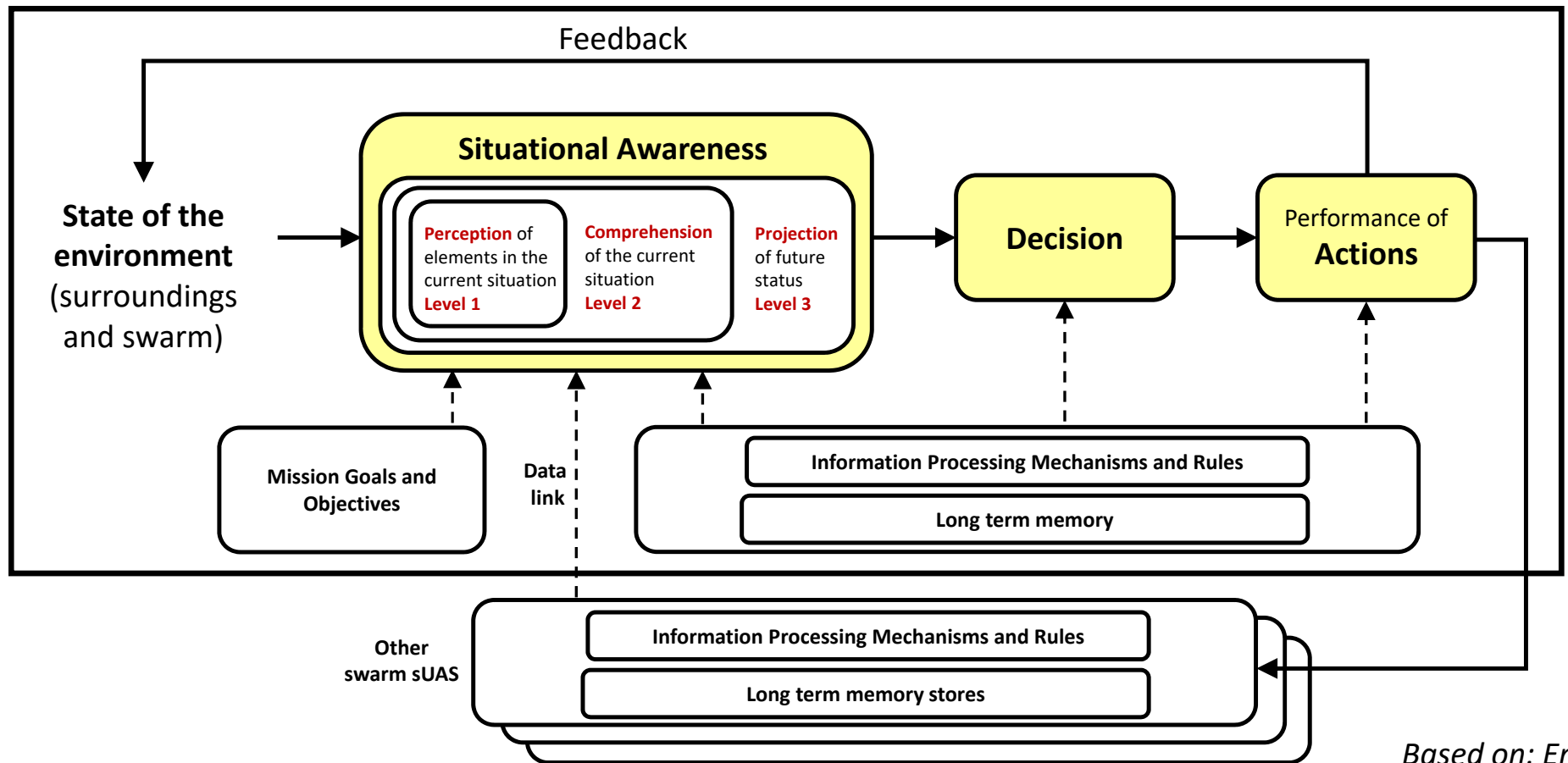
*A. M. Berdahl, et al., "Collective Animal Navigation and Migratory Culture: from Theoretical Models to Empirical Evidence," *Phil. Trans. R. Soc. B*37320170009, March 2018.

Swarm Navigation – Learning from Nature

- **emergent sensing:** the whole swarm produces a set of measurements that can be used to build a model of the environment (e.g., situational awareness) and help in the current or future navigation efforts .
- **social learning:** information existing with the individual swarm members is exchanged so the whole group can benefit.
- **collective learning:** where interactions within the group lead to better and more detailed knowledge of the environment and leading to better collision avoidance decisions and route choices that support the required navigation performance



Cognitive & Collaborative Processes: Dynamic Decision System



Based on: Endsley

Cognition: appropriate and adapted actions based on perception and knowledge

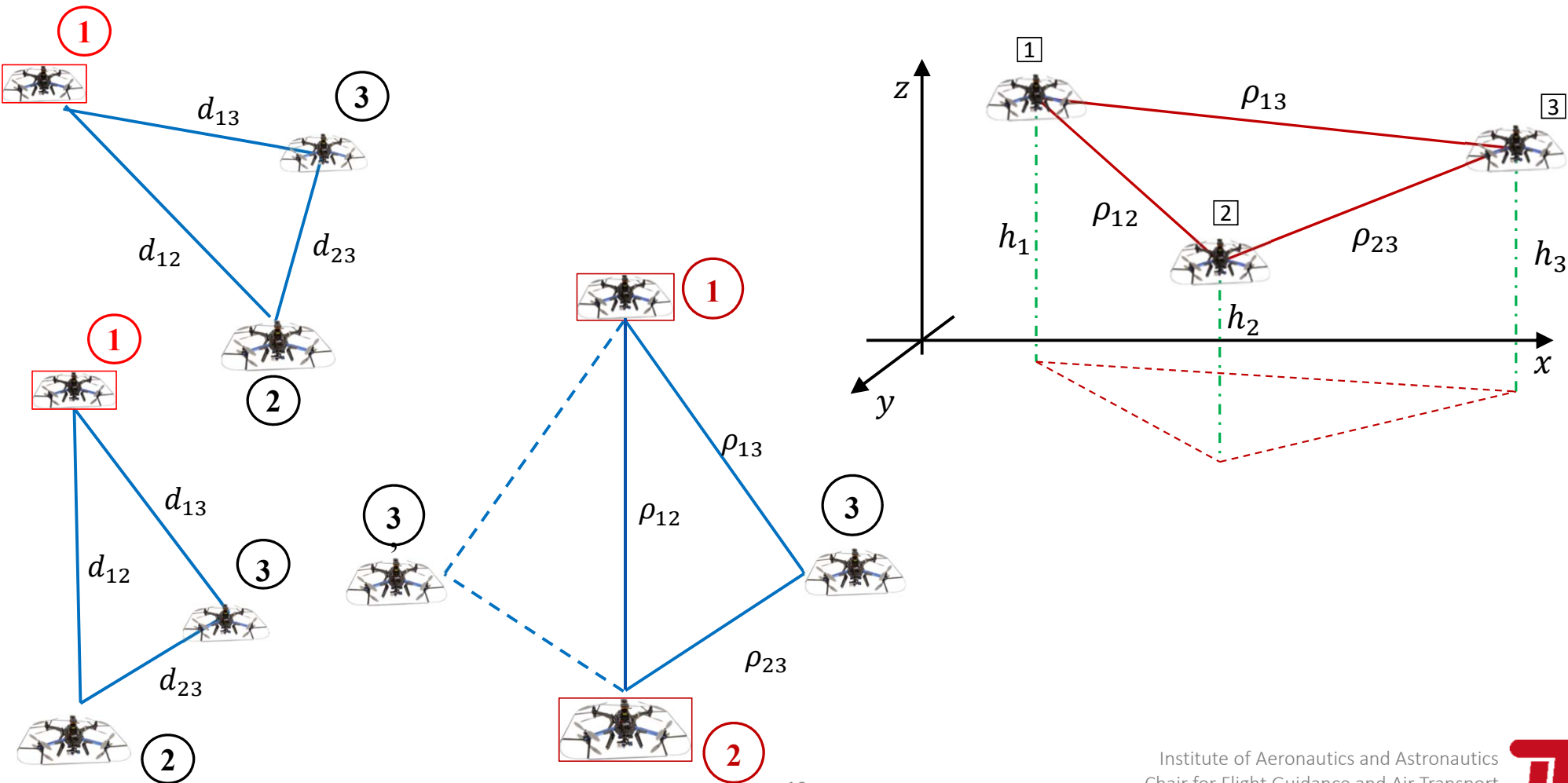
Collaboration: improved ability to reason and interact based on information exchange and spatial distribution

Perception: Sensor measurement examples

	Raw	Processed
GNSS	Pseudorange (ρ_i), carrier-phase (φ_i)	Position (\mathbf{r}_i), position change ($\Delta\mathbf{r}_i$)
Laser range scanners	Range (ρ_i), scan angle (α_i), point cloud	Position change ($\Delta\mathbf{r}_i$), orientation change ($\Delta\mathbf{C}_i$)
3D Imagers	Range (ρ_i), azimuth (α_i), elevation (θ_i), point cloud	Position change ($\Delta\mathbf{r}_i$), orientation change ($\Delta\mathbf{C}_i$)
Camera (mono)	Unit vector pointing to feature/pixel (\mathbf{e}_i)	Scaled position change ($\lambda\Delta\mathbf{r}_i$), orientation change ($\Delta\mathbf{C}_i$)
Camera (stereo)	Pairs of unit vector pointing to feature/pixel ($\mathbf{e}_i, \mathbf{e}_j$)	Position change ($\Delta\mathbf{r}_i$), orientation change ($\Delta\mathbf{C}_i$)
Range radios (e.g., Ultra-Wide Band beacons)	Relative range between 'i' and 'j' (ρ_{ij})	-
IMU	Acceleration/specific force (\mathbf{f}_i), angular rate ($\boldsymbol{\omega}_{nb}^b$)	Position (\mathbf{r}_i), velocity (\mathbf{v}_i), attitude ($\boldsymbol{\psi}_i$)
Optical flow	-	Scaled velocity ($\lambda\mathbf{v}_i$),
Altimeter	Height above ground (h_{AGL})	-
Baro altimeter	Height w.r.t. pressure reference height (h_{baro})	-
Magnetometer	Orientation w.r.t. magnetic field (\mathbf{m}_i)	-

sly

Comprehension: Exploiting Constraints



Comprehension and Projection: Filter Mechanizations

→ Snapshot approaches:

- ordinary least squares (OLS),
- weighted least squares (WLS), etc.

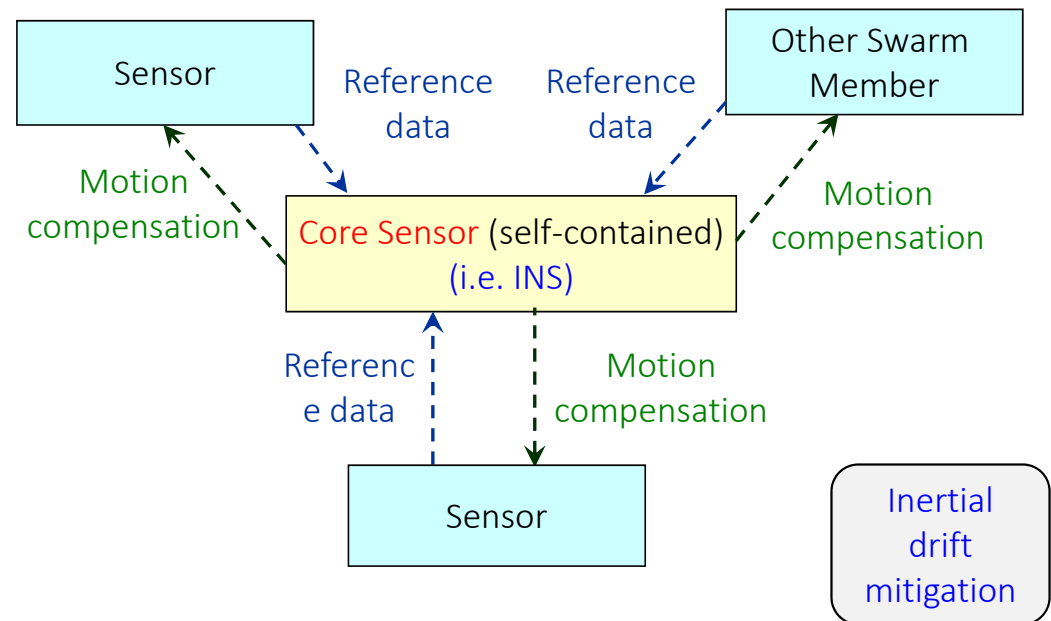
→ Sequential estimators:

- Kalman Filters (KF),
- Extended Kalman filters (EKF),
- Particle Filters (PF)
- Multiple Mode Filters, etc.

→ Batch estimators:

- Least squares “fitting” methods
- Solvers such as non-linear least squares solvers, etc. (g2o, Ceres, ...)

The key is:



Case I: Inertial/Range-radio/Baro Integration



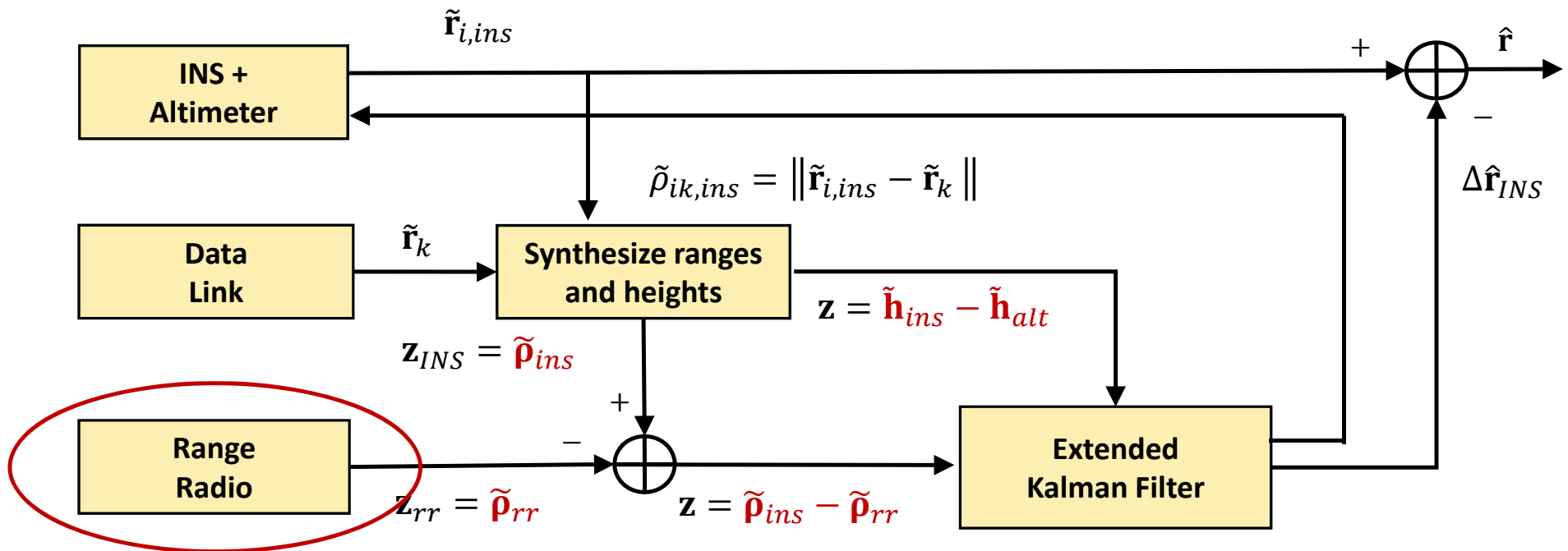
- **Platform A** with a Sensor STIM300 and a Novatel OEM-615;
- **Platform B** with a VectorNav VN-100 and Xsens Mti-1 inertial and a Novatel OEM-615 GNSS receiver, and
- **Platform C** with an Xsens Mti-1 and a U-blox M8T

Filtered GNSS trajectories of 6 cooperative UAS platforms



Range-radio was simulated but based on a system that was finalized after the flight test

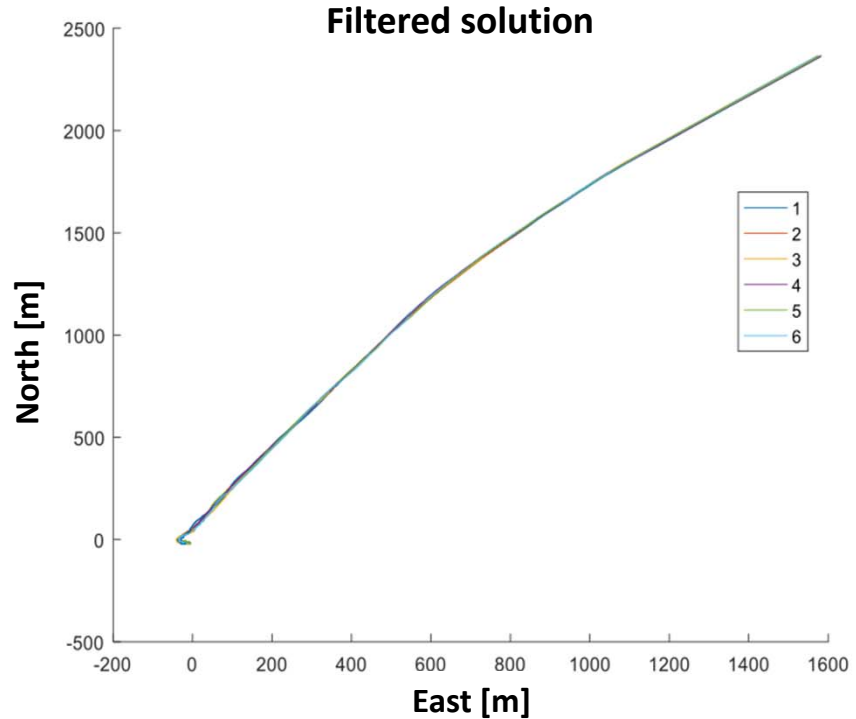
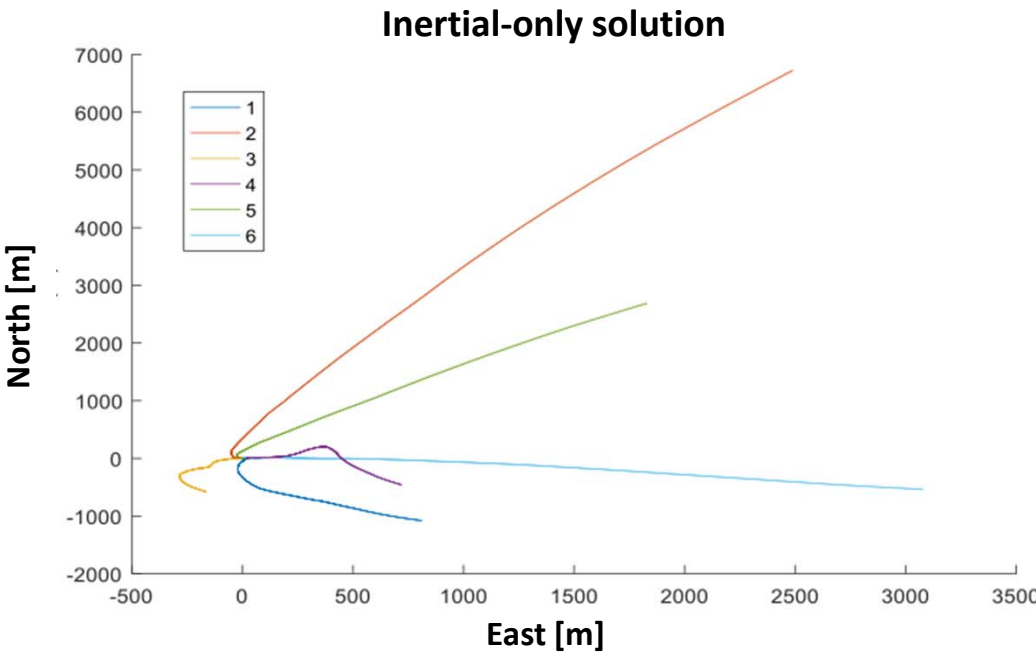
Case I: Inertial/Range-radio/Baro Integration



$$\tilde{\rho}_{ik,ins} \approx \rho_{ik} + \frac{\mathbf{s}_{ik}^T}{\rho_{ik}} \delta \mathbf{r}_{ik,ins} = \rho_{ik} + \underbrace{\mathbf{u}_{ik}^T}_{\delta \rho_{ik,ins}} \delta \mathbf{r}_{ik,ins}$$

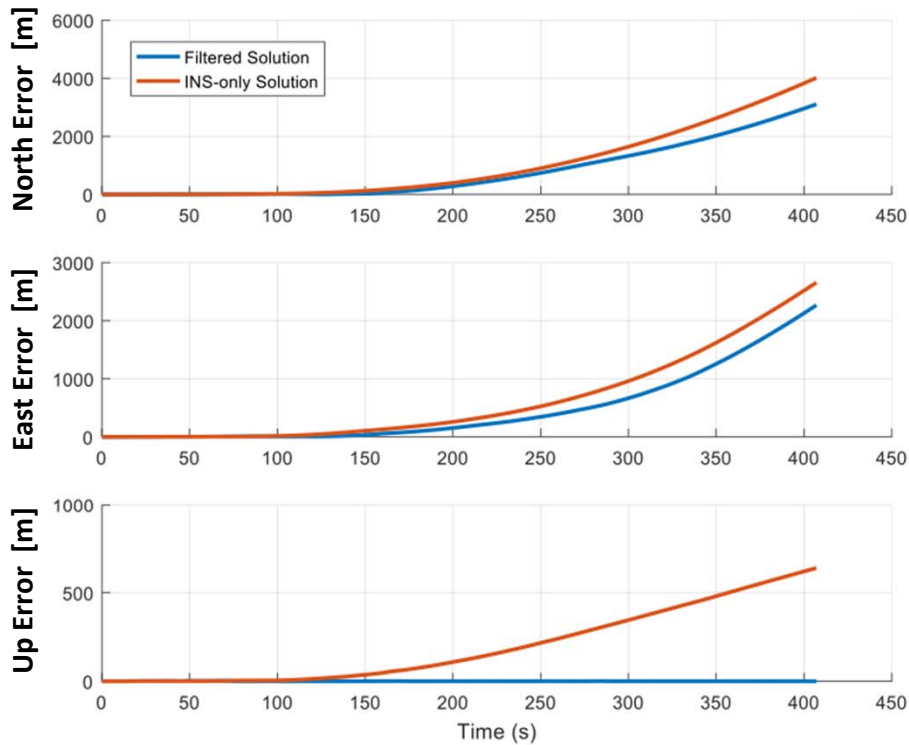
$$\begin{aligned} z_{ik} &= \tilde{\rho}_{ik,uwb} - \tilde{\rho}_{ik,ins} \approx -\mathbf{u}_{ik}^T \delta \mathbf{r}_{ik,ins} + v_{ik} \\ z_{alt,k} &= h_{k,ins} - h_{k,alt} = \delta r_{kz,ins} + v_{baro} \end{aligned}$$

Case I Results – Inertial Solutions

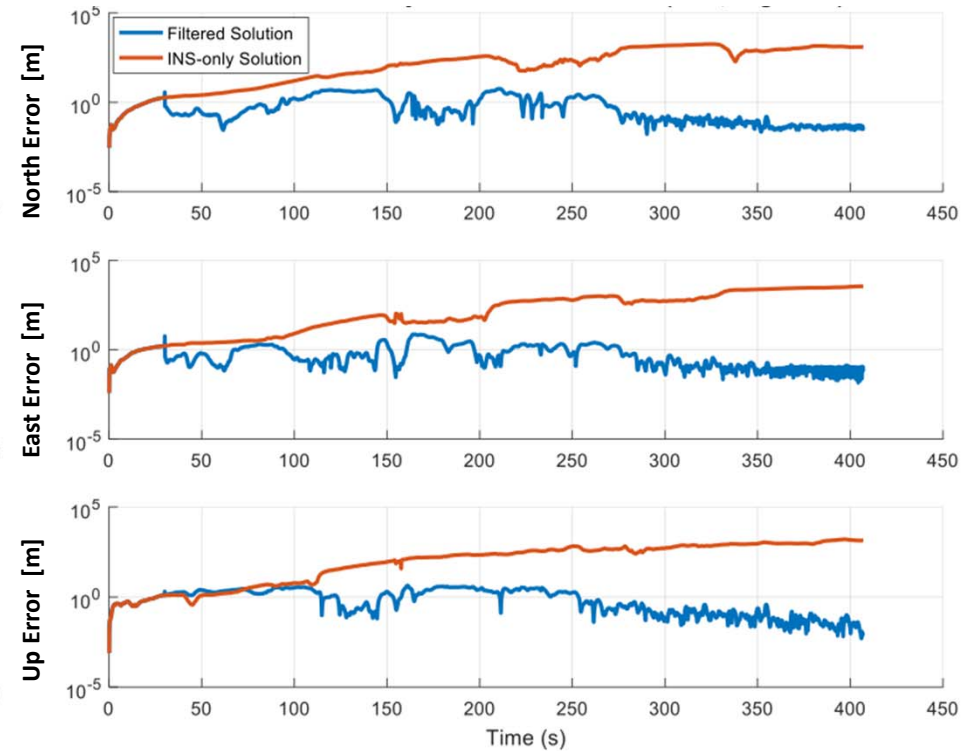


Case I Results – Inertial Solutions

Absolute position solution errors

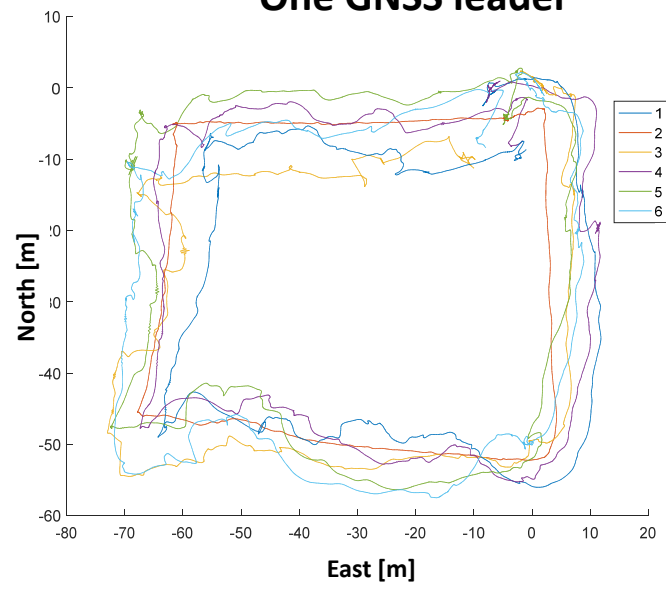


Relative position solution errors (log-y scale)

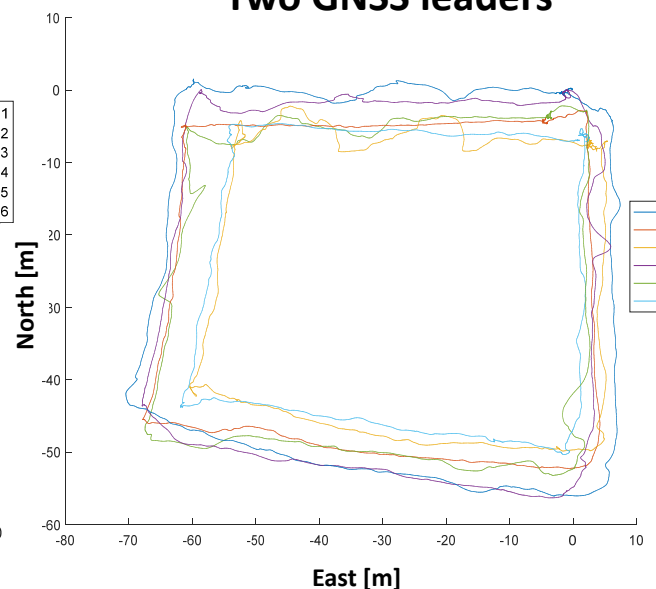


Case I: Use of Leaders

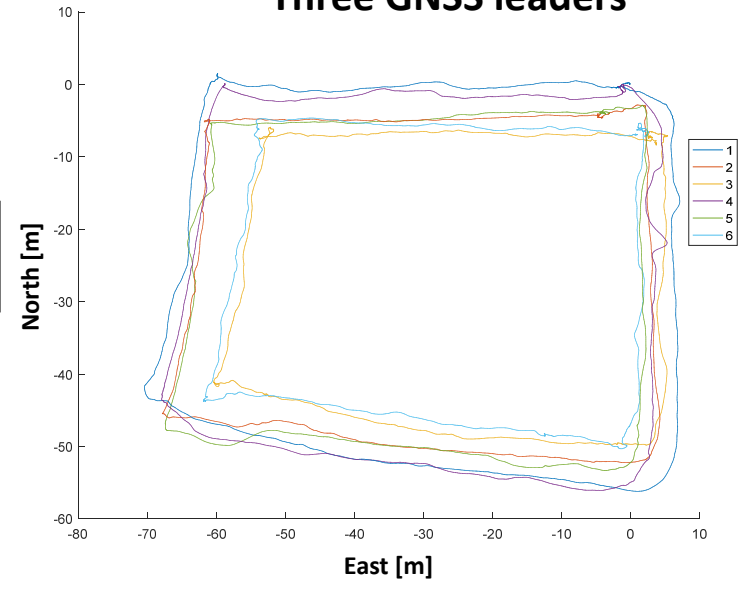
One GNSS leader



Two GNSS leaders



Three GNSS leaders



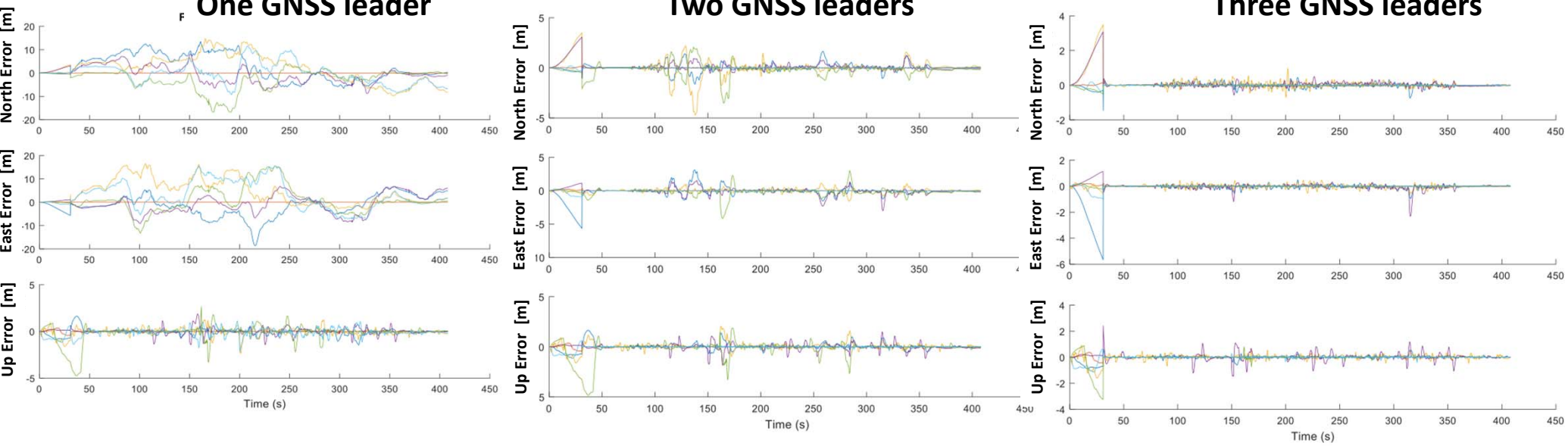
With one leader, the "swarm" can still make "local" rotations

Case I: Use of Leaders

One GNSS leader

Two GNSS leaders

Three GNSS leaders



Case II and III: Inertial/Range-radio/Beacon Integration

- UAVs operating in a (GNSS-challenged) urban environment
- UAV equipment list:

	Equipment	1	2	3	4	5	6	7	8
Case II	IMU	√	√	√	√	√	√	n/a	n/a
	Baro	√	√	√	√	√	√	n/a	n/a
	Beacon	√	-	-	√	-	-	n/a	n/a
	Range-radio	√	√	√	√	√	√	n/a	n/a
	GNSS	-	-	-	-	-	-	n/a	n/a
Case III	IMU	√	√	√	√	√	√	√	√
	Baro	√	√	√	√	√	√	√	√
	Beacon	-	-	-	-	-	-	-	-
	Range-radio	√	√	√	√	√	√	√	√
	GNSS	-	-	-	-	-	-	√	√

- The data for UAV 1 through 6 is based on the Case I flight test with real IMU and baro data; GNSS constellation just “moved” to urban environment (Berlin)

Case II and III: Inertial/Range-radio/Beacon Integration

→ Algorithms under the test include

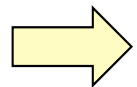
- INS standalone
- Beacon/baro OLS,
- Beacon/baro/ INS KF
- RR/INS/INS/baro + Leader NLSolver

→ Non-linear solver:

- Measurement equation – log-likelihood function

$$\begin{aligned}\log\{p(\mathbf{z}|\mathbf{x})\} &= \log(\eta) + [\mathbf{z} - \mathbf{h}(\mathbf{x})]^T \boldsymbol{\Sigma}_v^{-1} [\mathbf{z} - \mathbf{h}(\mathbf{x})] \Rightarrow \\ \log\{p(\mathbf{z}|\mathbf{x})\} &\propto [\mathbf{z} - \mathbf{h}(\mathbf{x})]^T \boldsymbol{\Sigma}_v^{-1} [\mathbf{z} - \mathbf{h}(\mathbf{x})]\end{aligned}$$

- For measurement set $\mathcal{S} = \{\mathbf{z}_i | i = 1, \dots, N\}$ of measurements



$$\hat{\mathbf{x}} = \arg \min_{\mathbf{x}} \mathbf{F}(\mathbf{x})$$

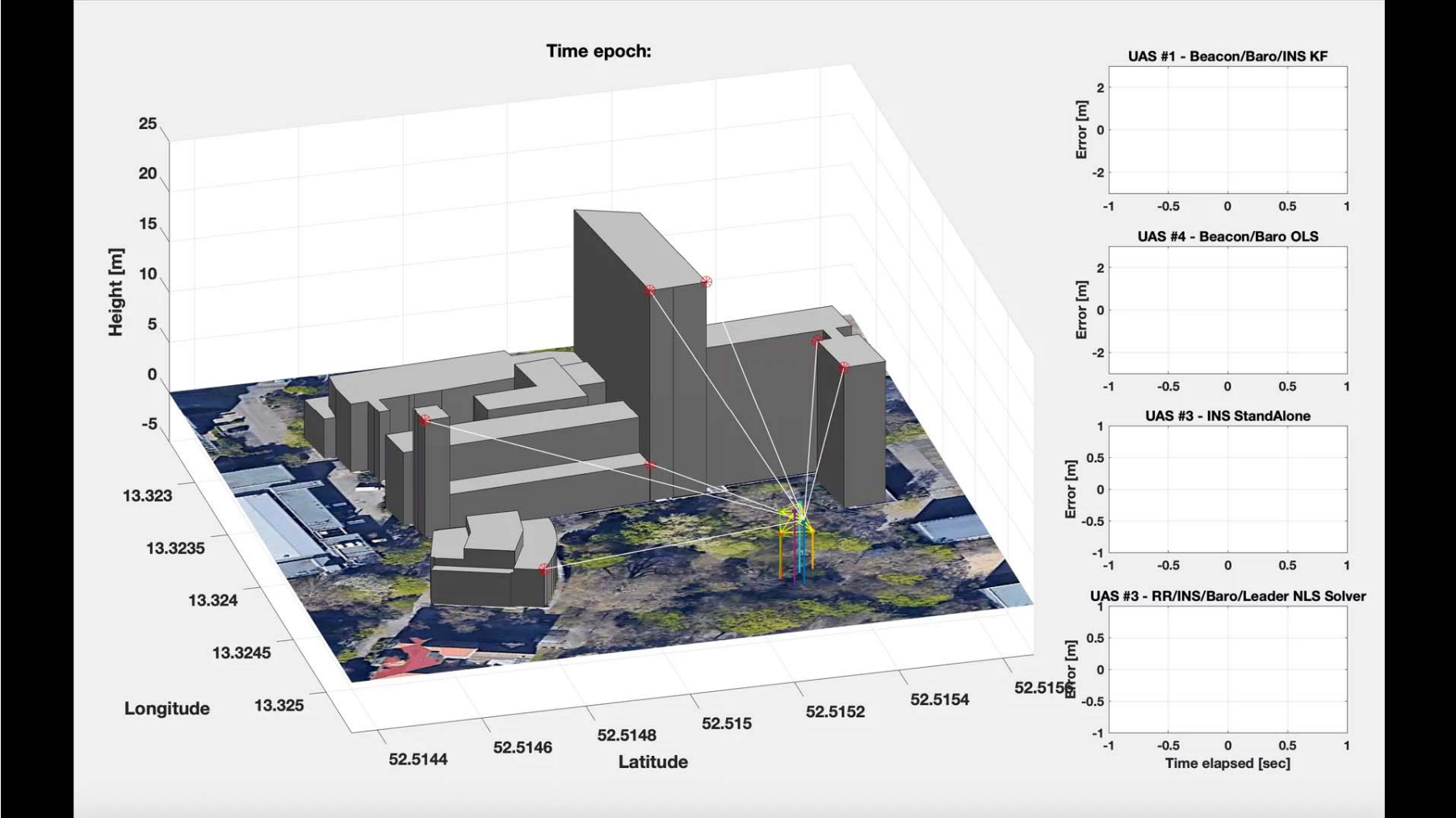
$$\mathbf{F}(\mathbf{x}) = \sum_{\mathbf{z}_i \in \mathcal{S}} [\mathbf{z}_i - \mathbf{h}_i(\mathbf{x})]^T \boldsymbol{\Sigma}_{v_i}^{-1} [\mathbf{z}_i - \mathbf{h}_i(\mathbf{x})]$$

$$F_{rr,1}(\mathbf{x}) = \frac{1}{\sigma_v} [\|\mathbf{x} - \mathbf{r}_{lead,1}\| - \tilde{\rho}_{i,1}]$$

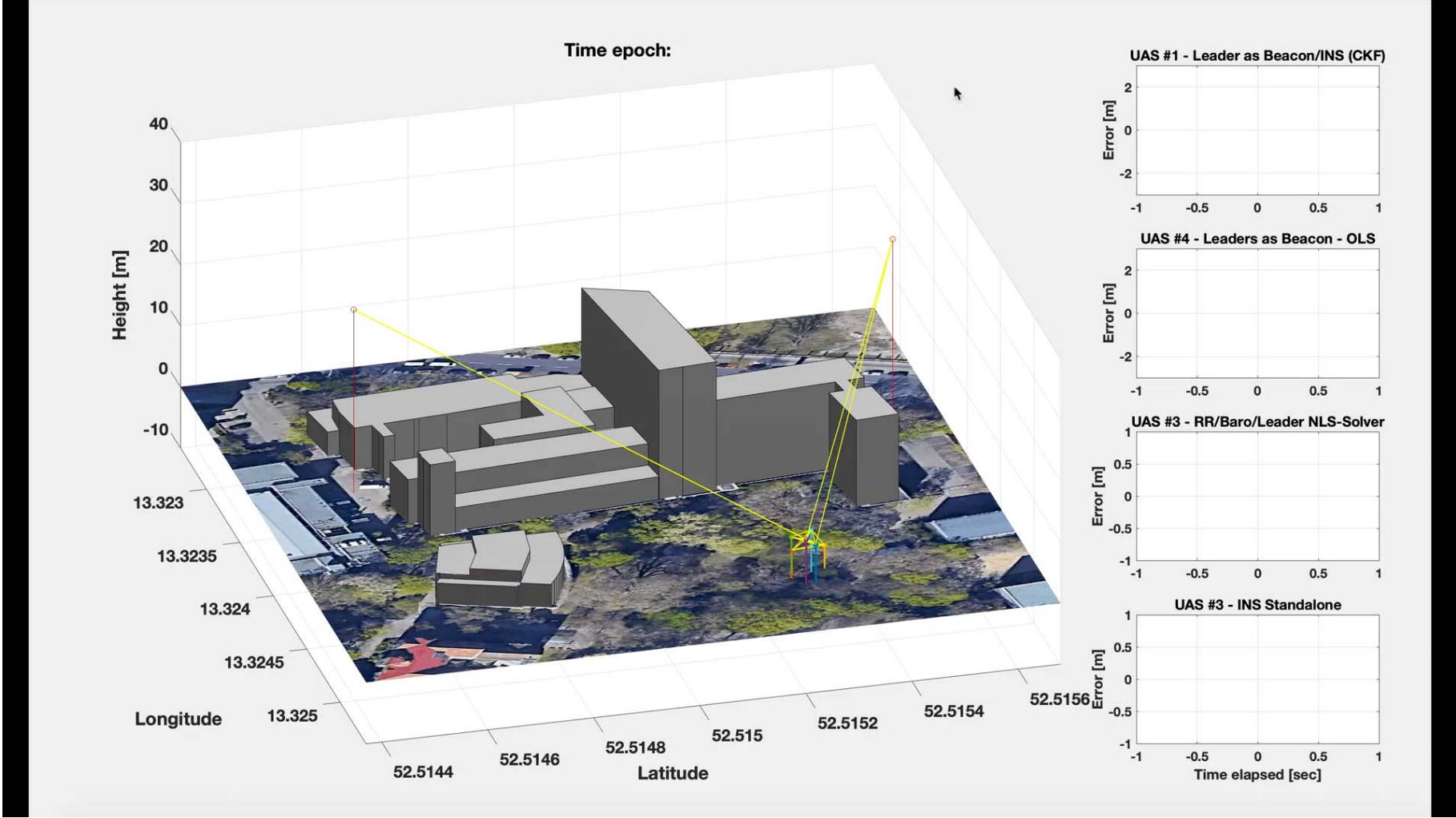
$$F_{rr,4}(\mathbf{x}) = \frac{1}{\sigma_v} [\|\mathbf{x} - \mathbf{r}_{lead,4}\| - \tilde{\rho}_{i,4}]$$

$$F_{h,1}(\mathbf{x}) = \frac{1}{\sigma_{alt}} [z - h_{alt}]$$

Case II Results



Case III Results



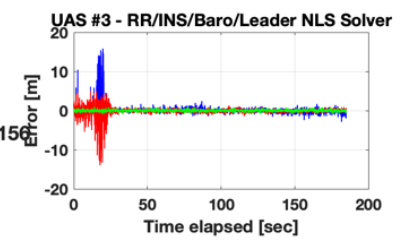
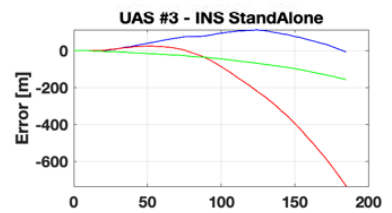
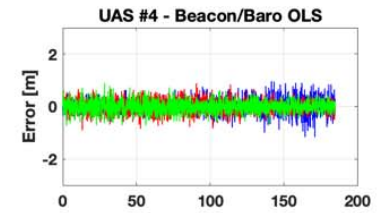
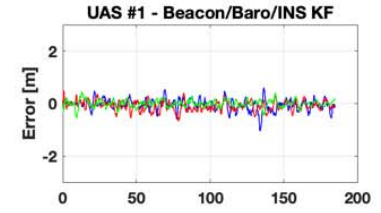
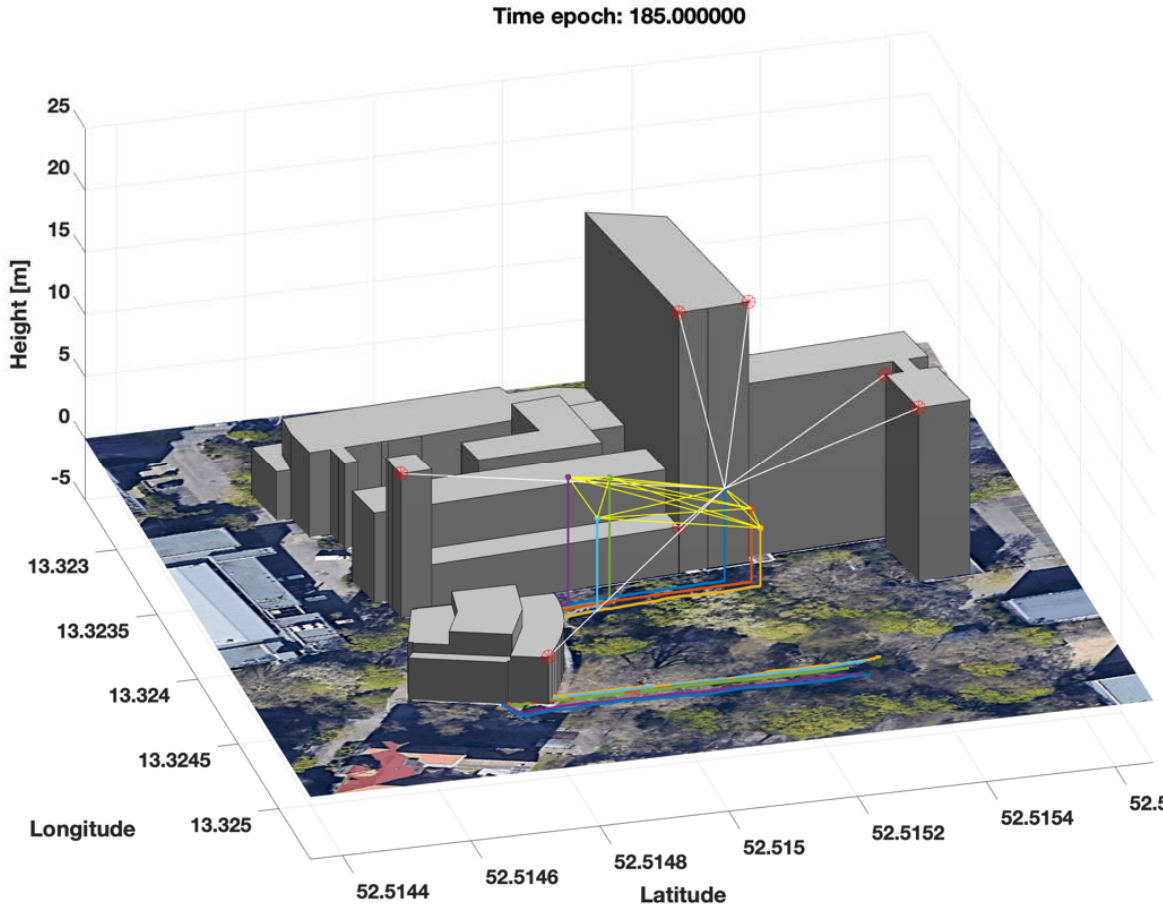
Summary and Conclusions

- ➔ Setup a cognition and collaboration approach to absolute and relative navigation of sUAS swarms, in part, on some basic principles of swarm navigation in nature .
- ➔ Results from a flight test and a simulation demonstrated that the leadership and social learning principles do apply nicely and that by evaluating the necessary constraints filters can be defined that allow some of the swarm members to operate in GNSS-challenging environments .
- ➔ So far, focus on the accuracy performance of the navigation solution; next steps will address the inclusion of other navigation performance parameters (i.e., integrity, continuity, and availability)



Questions?

Case II Results



Case III Results

