

# Methods of Trajectory Estimation in Challenging Mapping Scenarios

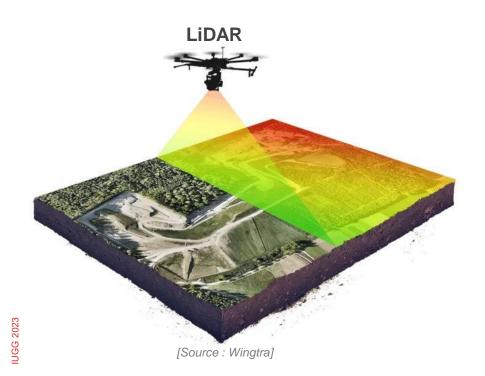
**IUGG 2023 Berlin** 

G05f - Multi-signal positioning, Remote Sensing and Applications

Aurélien Brun

### **EPFL Motivation**

#### **Challenges in LiDAR mapping technology**



Direct georeferencing & Continuous capture

Trajectory must be accurately determined at all times

### **EPFL Motivation**

#### Challenges in LiDAR mapping technology

Trajectory must be accurately determined at all times

What if we use a drone with low grade navigation sensor?

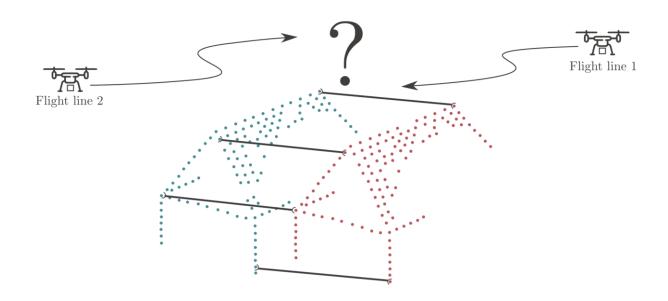
What if we lose GNSS signal?

What if we miscalibrate our system?

### **EPFL** How to improve LiDAR reliability?

We propose a novel LiDAR based trajectory adjustment procedure:

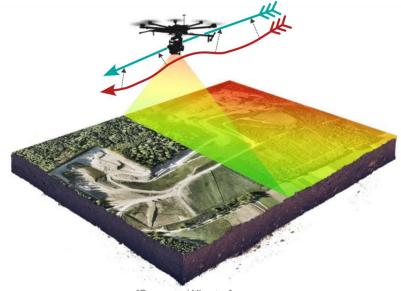
1. Robust pipelines to establish point to point correspondences in point clouds



### **EPFL** How to improve LiDAR reliability?

We propose a novel LiDAR based trajectory adjustment procedure:

- Robust pipelines to establish point to point correspondences in point clouds
- Adjustment step to refine the entire trajectory, calibrate system mounting

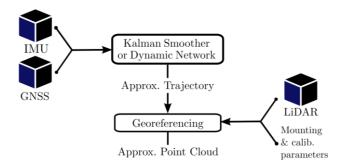


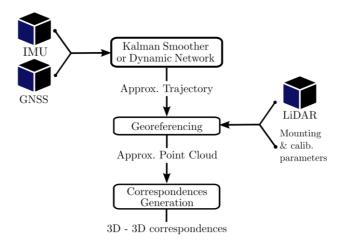
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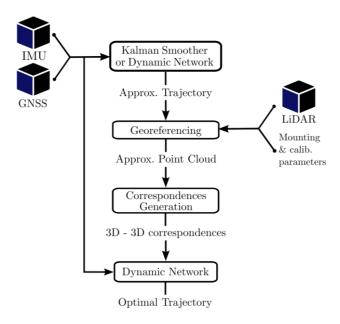
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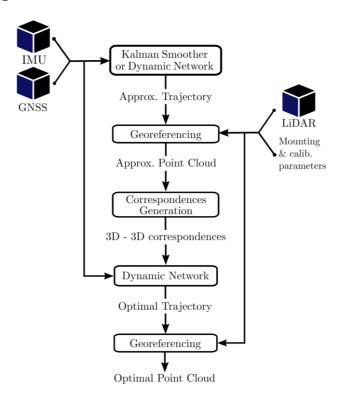
- 1. Robust pipelines to establish point to point correspondences in point clouds
- 2. Adjustment step to refine the entire trajectory, calibrate system mounting

Objectives: allow post processing system calibration & trajectory correction, specifically when GNSS outages occur

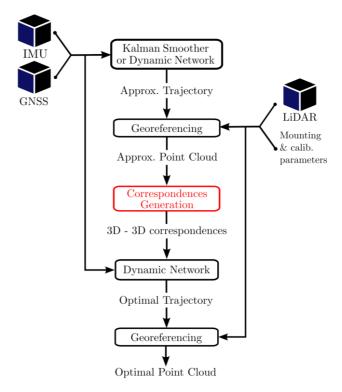




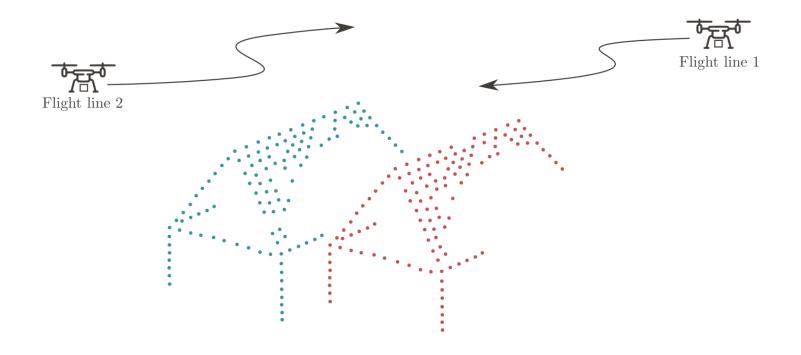




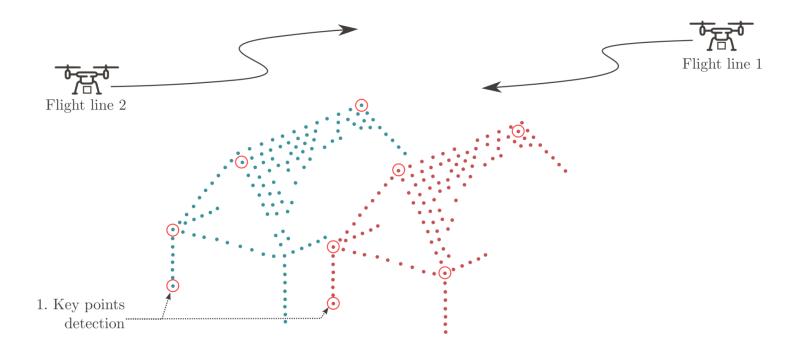
#### Point to point correspondences generation



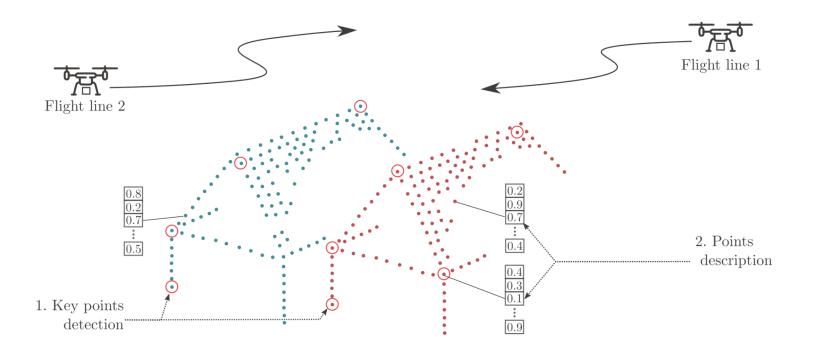
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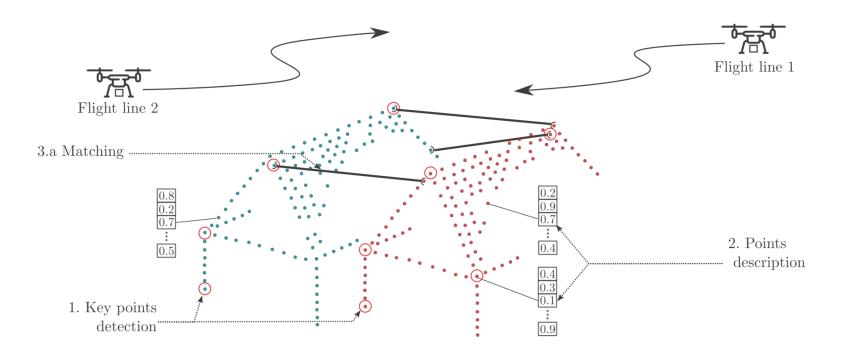
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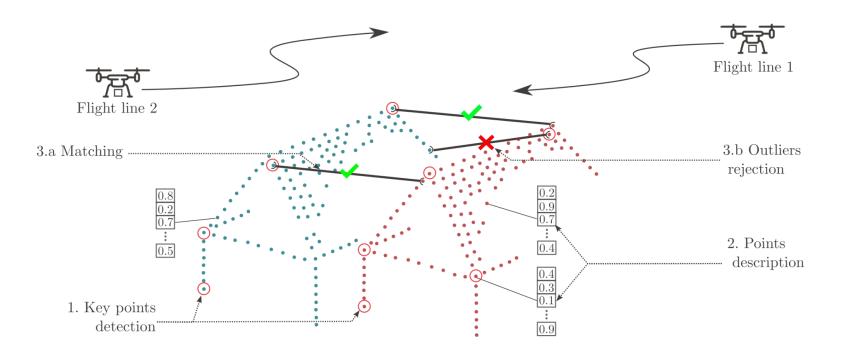
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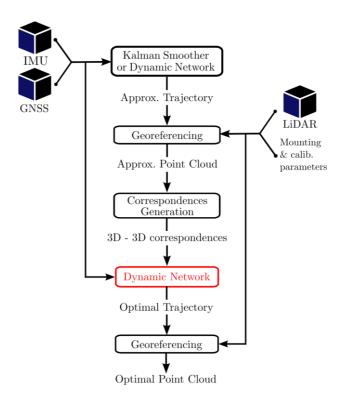
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## EPFL Methods Dynamic Network



An extension of conventional geodetic networks:

Optimal solving of all trajectory parameters and their derivatives at once (e.g. specific forces + angular velocities) → ~300k parameters to solve per minute of trajectory¹

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- 2. Direct integration of spatial constraints, e.g. image tie points<sup>2,3</sup> & LiDAR point to point →increase redundancy and improve numerical stability

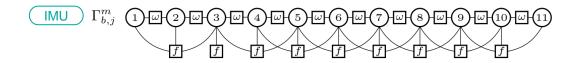
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- 2. Direct integration of spatial constraints, e.g. image tie points<sup>2,3</sup> & LiDAR point to point →increase redundancy and improve numerical stability
- 3. Target the source of the errors (e.g. IMU biases) rather than the consequences (i.e. their projection on the orientation)

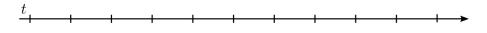


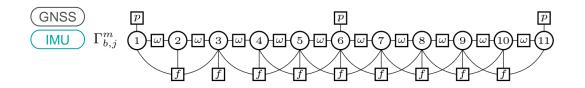
 $\Gamma^m_{b,j}$  (1) (2) (3) (4) (5) (6) (7) (8) (9) (10) (11)



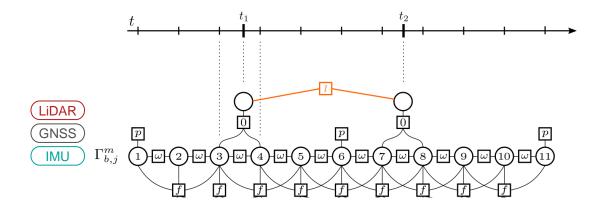


## EPFL Methods Dynamic Network





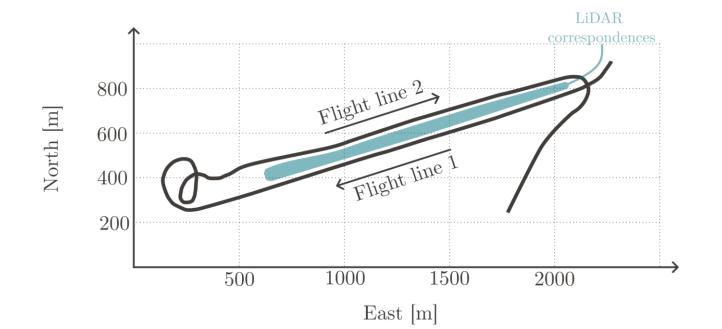
## EPFL Methods Dynamic Network



## **Setup**Aerial - Nominal Scenario

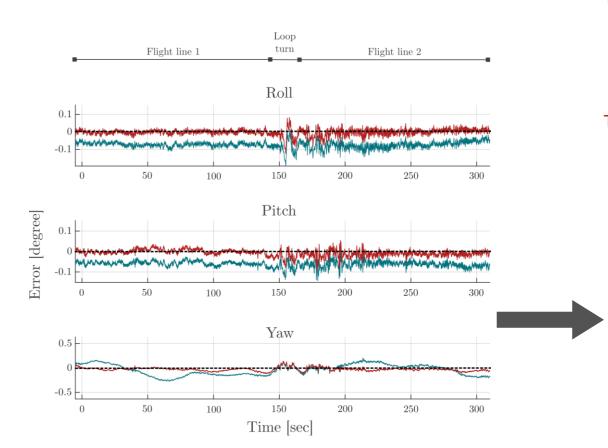


- Flight duration ~ 5 minutes
- Precise laser & UAV grade IMU → large attitude errors
- Navigation grade (~ ground truth) trajectory available



### **EPFL** Results

#### **Aerial - Nominal Scenario**





T. 1 attitude error

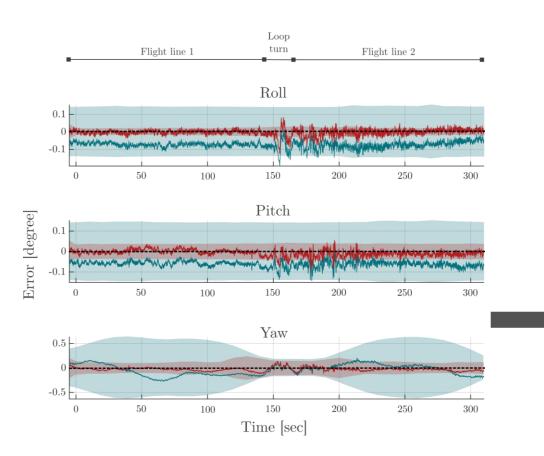
Trajectory. 2 GNSS IMU LiDAR

T. 2 attitude error

 Errors reduced by a factor 3→5 (attitude and subsequent point cloud)

### **EPFL** Results

#### **Aerial - Nominal Scenario**





T. 1 attitude error

T. 1 3σ confidence interval

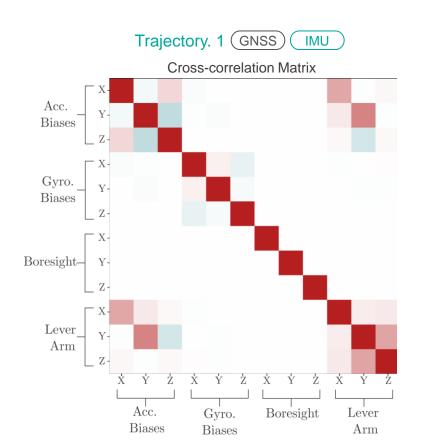
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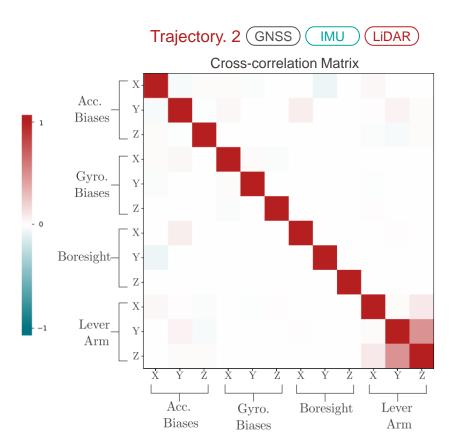
T. 2 attitude error

T. 2 3σ confidence interval

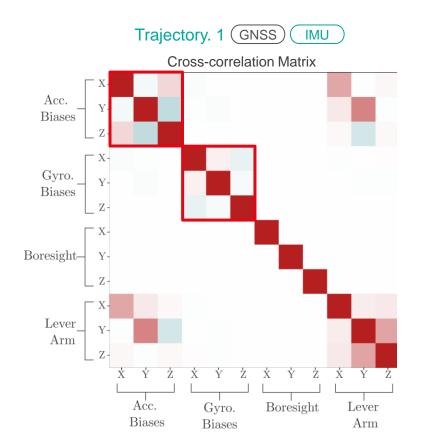
- Errors reduced by a factor 3→5 (attitude and subsequent point cloud)
- A posteriori confidence largely improved

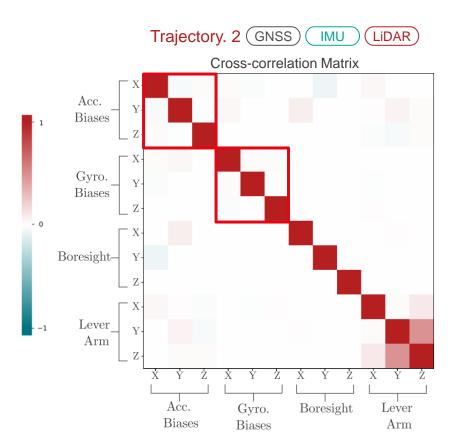
## **EPFL Results**Aerial - Nominal Scenario



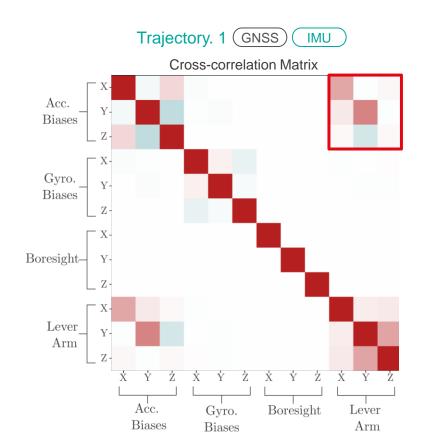


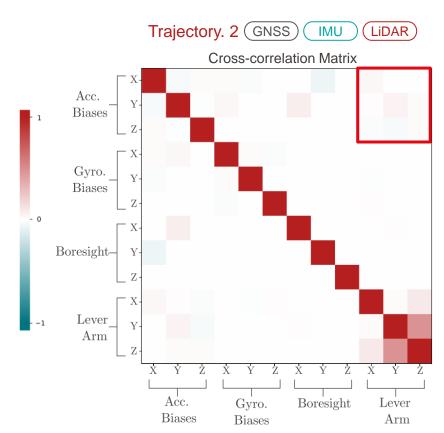
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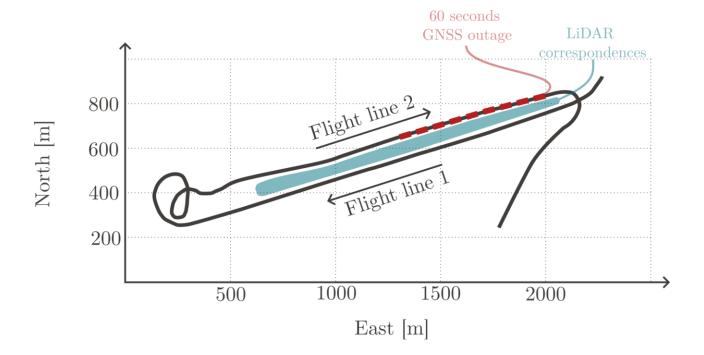




## **Setup**Aerial - GNSS Outage

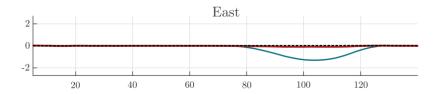


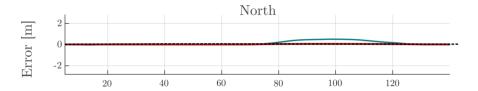
- Flight duration ~ 5 minutes
- GNSS Outage → large position errors
- Navigation grade (~ ground truth) trajectory available

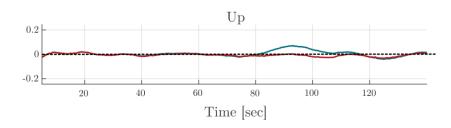


## **Results**Aerial - GNSS Outage













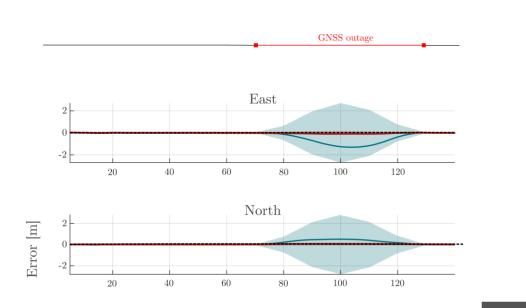


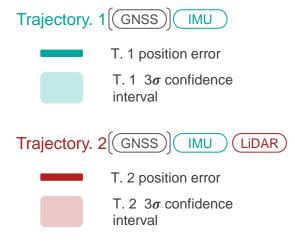


 Max. errors reduced by a factor 10→15 (position and subsequent point cloud)

## EPFL Results

#### **Aerial - GNSS Outage**

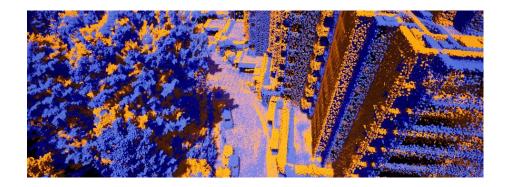




- Max. errors reduced by a factor
   10→15
   (position and subsequent point cloud)
- Quality and confidence inside the outage maintained comparable to outside of it

### **EPFL** Conclusion

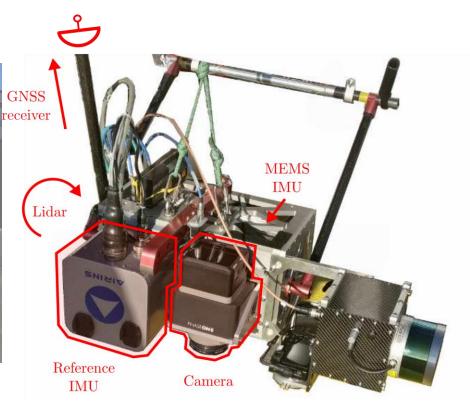
- Point to point correspondences in Dynamic Network improve significantly trajectory estimation
- Allow estimating unknown mounting parameters (i.e. lever-arm + boresight) up to certain accuracy
- Application to other navigation scenarios, e.g. indoor SLAM ...



### **Supplementary slides**

### **EPFL** Setup

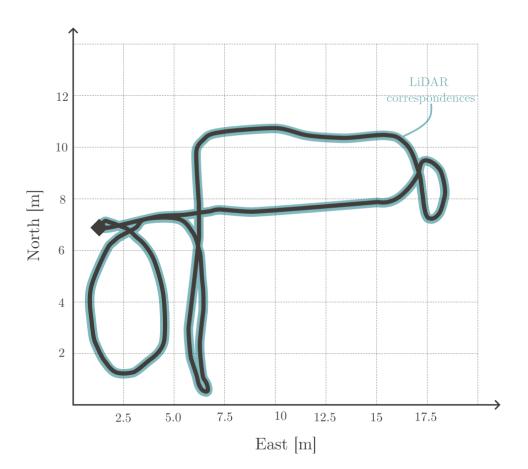




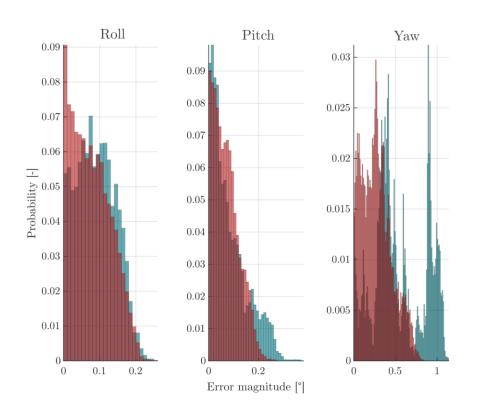
## **Setup** Indoor (on-going)

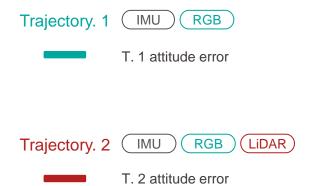
Trajectory 1 IMU RGB
Trajectory 2 IMU RGB LiDAR

Scan duration ~2.2 minutes

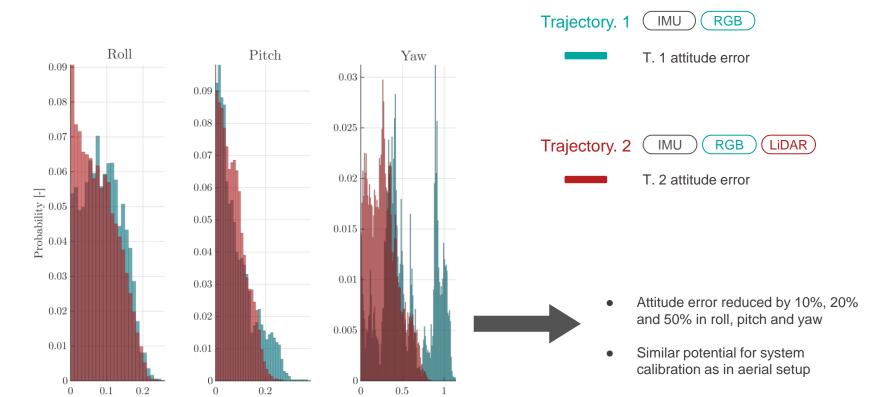


## Results Indoor- GNSS denied





## Results Indoor- GNSS denied



Error magnitude [°]

### **EPFL** Supplementary

#### **LiDAR Soft constraint**

