Institut de Robòtica i Informàtica Industrial

CSIC

UNIVERSITAT POLITÈCNICA DE CATALUNYA BARCELONATECH

Perception and Map Building for Inspection with Aerial Robots

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ERF2018 Workshop on Aerial Robotics Inspection

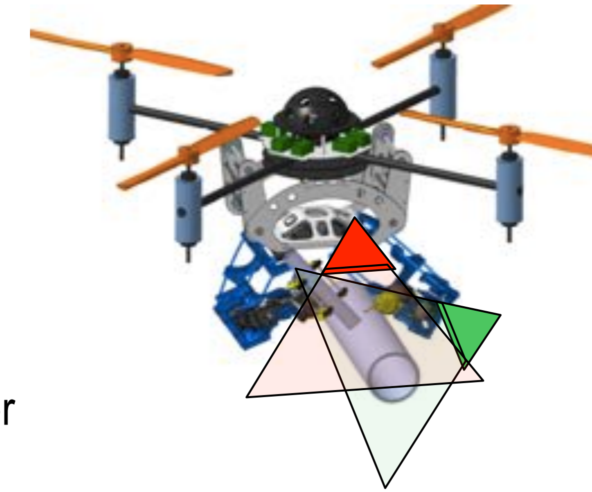
Tampere

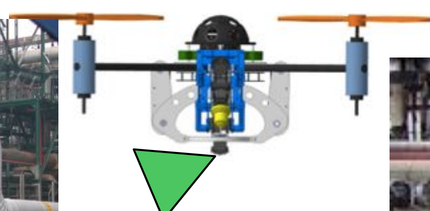
13/3/2018

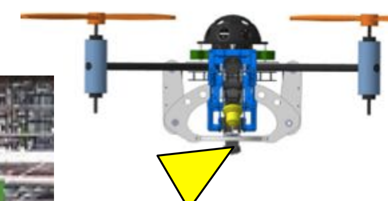
AEROARMS

AEROARMS Perception Objectives

The **main objective** of the Perception is to provide the needed perception functionalities to allow a reliable and accurate localization of the aerial robot for grabbing and manipulation.







Perception Objectives for Inspection and Maintenance

Navigation: To move from the origin to destination without colliding with static and dynamic objects

Localization and Mapping: Create a global or local map and obtain the pose of the aerial robot

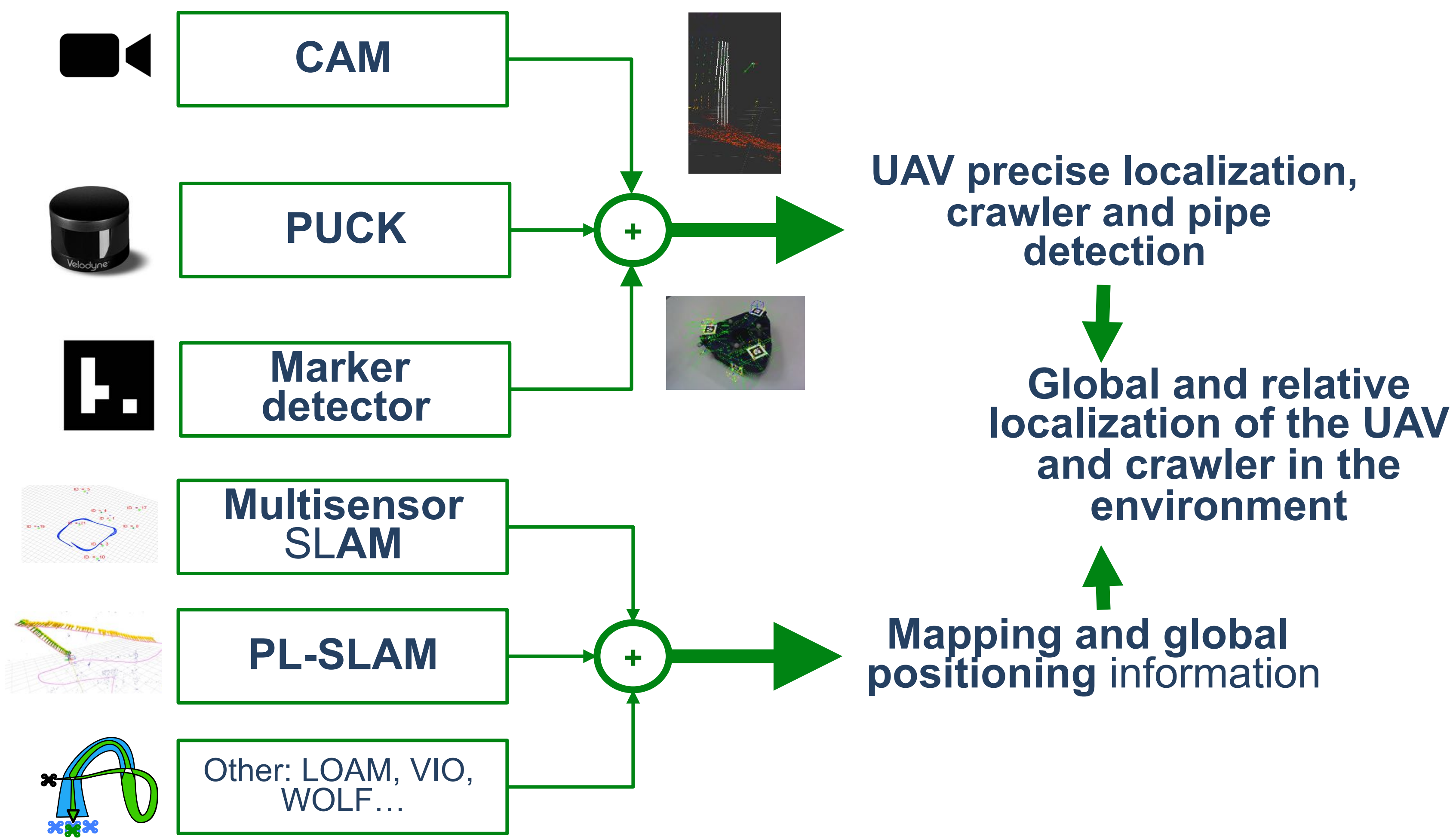
Object tracking: Track the object for inspection, drilling, grasping, manipulation, etc.

Object/area identification: Identify the objects for inspection, manipulation, landing, etc.

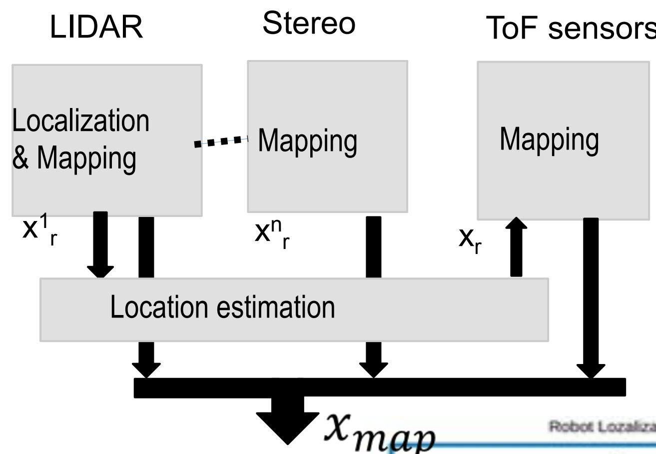
Perception fusion: Use multiple perception systems for inspection and maintenance tasks

Note: Work done by UPC and USE

Global and Relative Mapping and Localization system

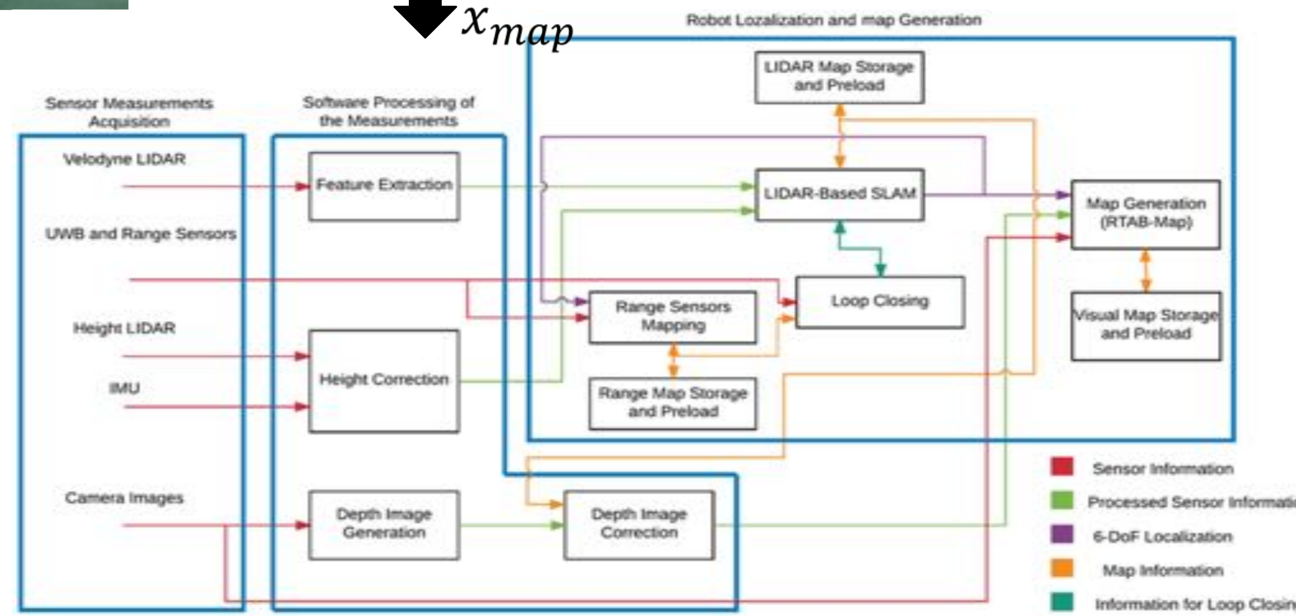


Multi-sensor Mapping (3D LIDAR, Stereo and ToF sensors)

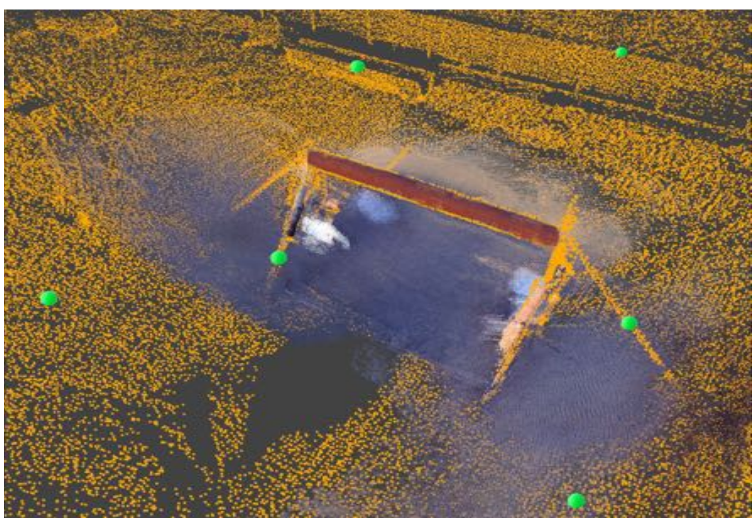


- Velodyne HDL-32E
- ZED stereo camera
- ToF range sensors
- UWB ToF sensors

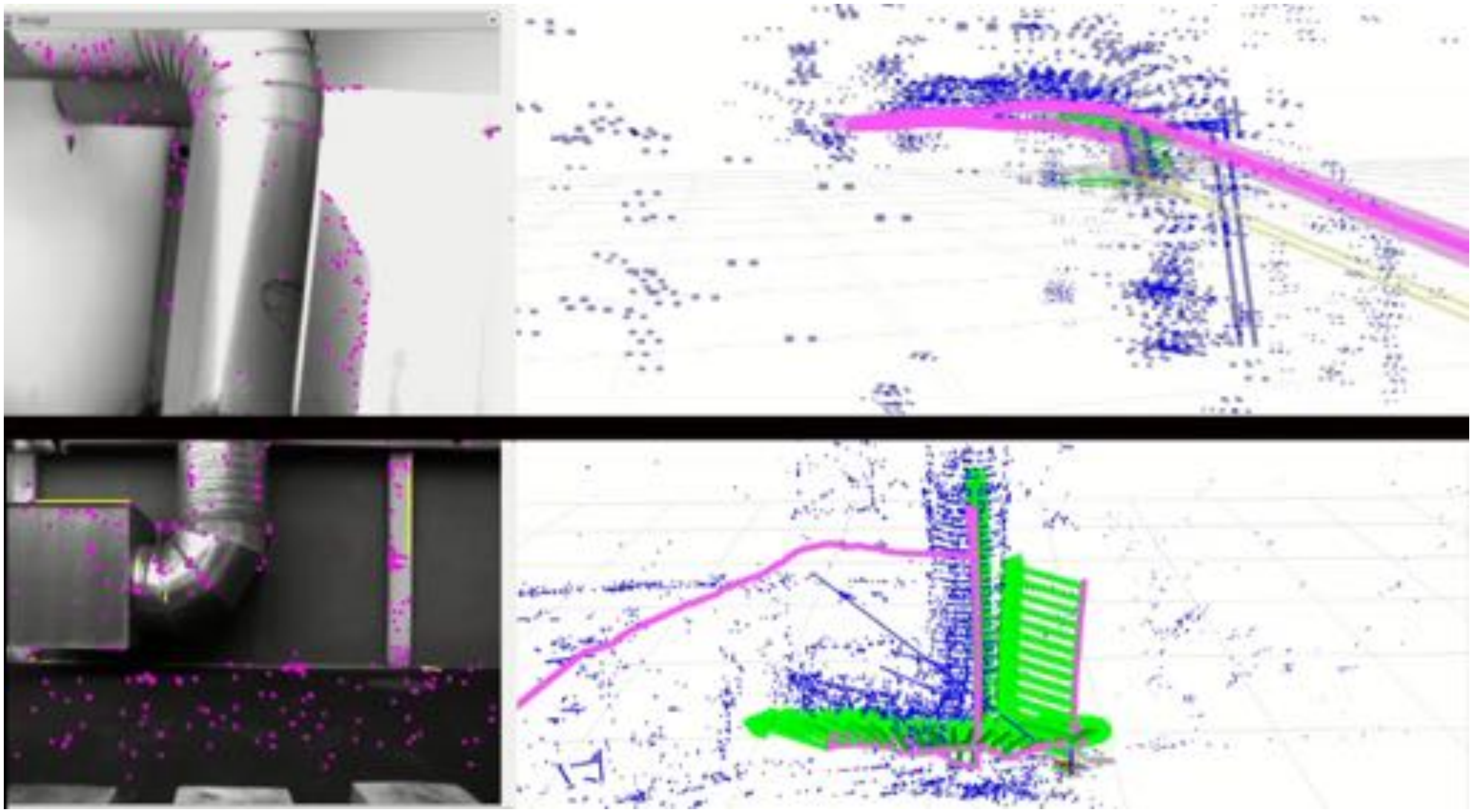
- Intel NUC NUC6i7KYK2 i7
- Jetson TX2



Global Localization and Mapping

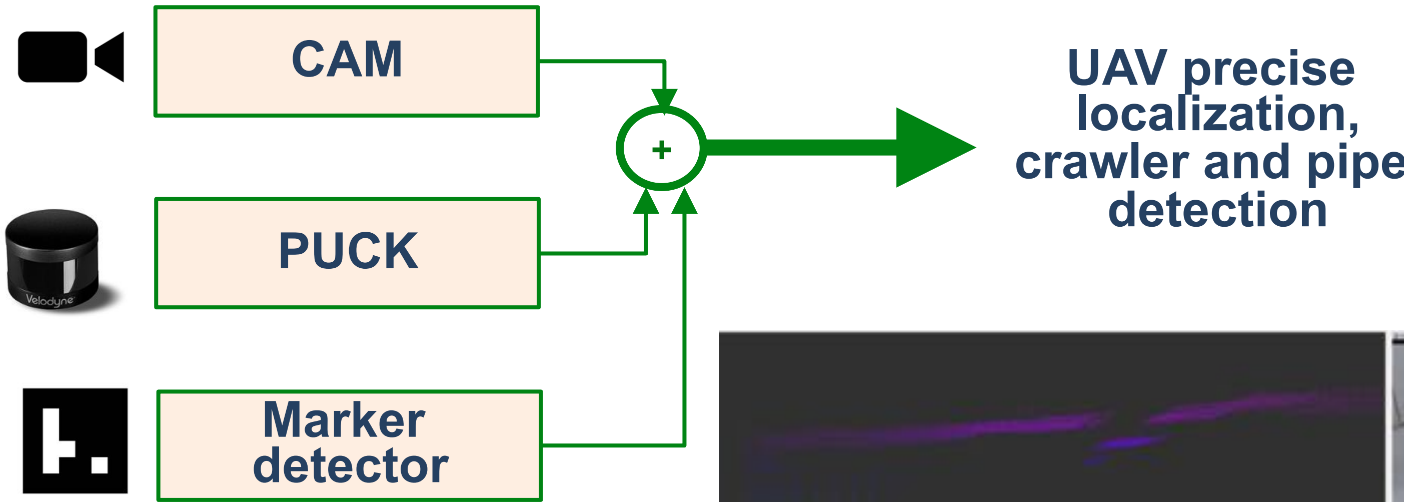


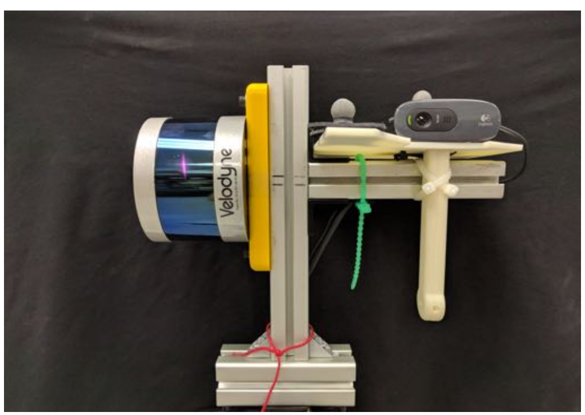
PL-SLAM for Local Positioning, Mapping and Pose Detection

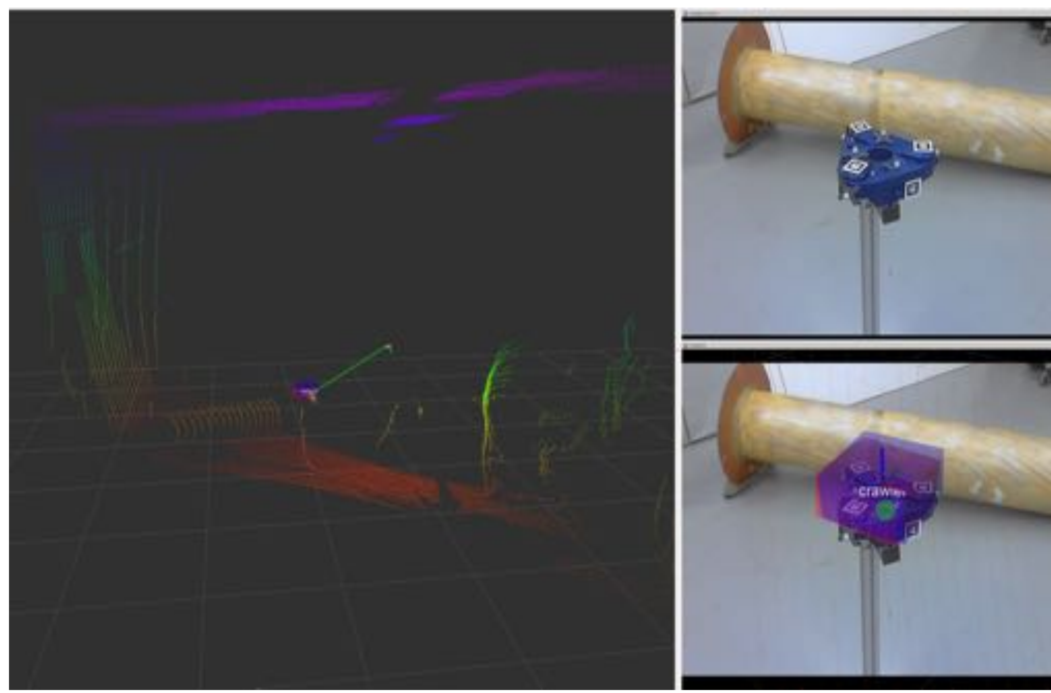


Real-Time Monocular Visual SLAM with Points and Lines (UPC) ICRA17'

UAV Localization, Crawler and Pipe Detection (cam, markers, puck)







Re-localization using Deep Learning (DL)

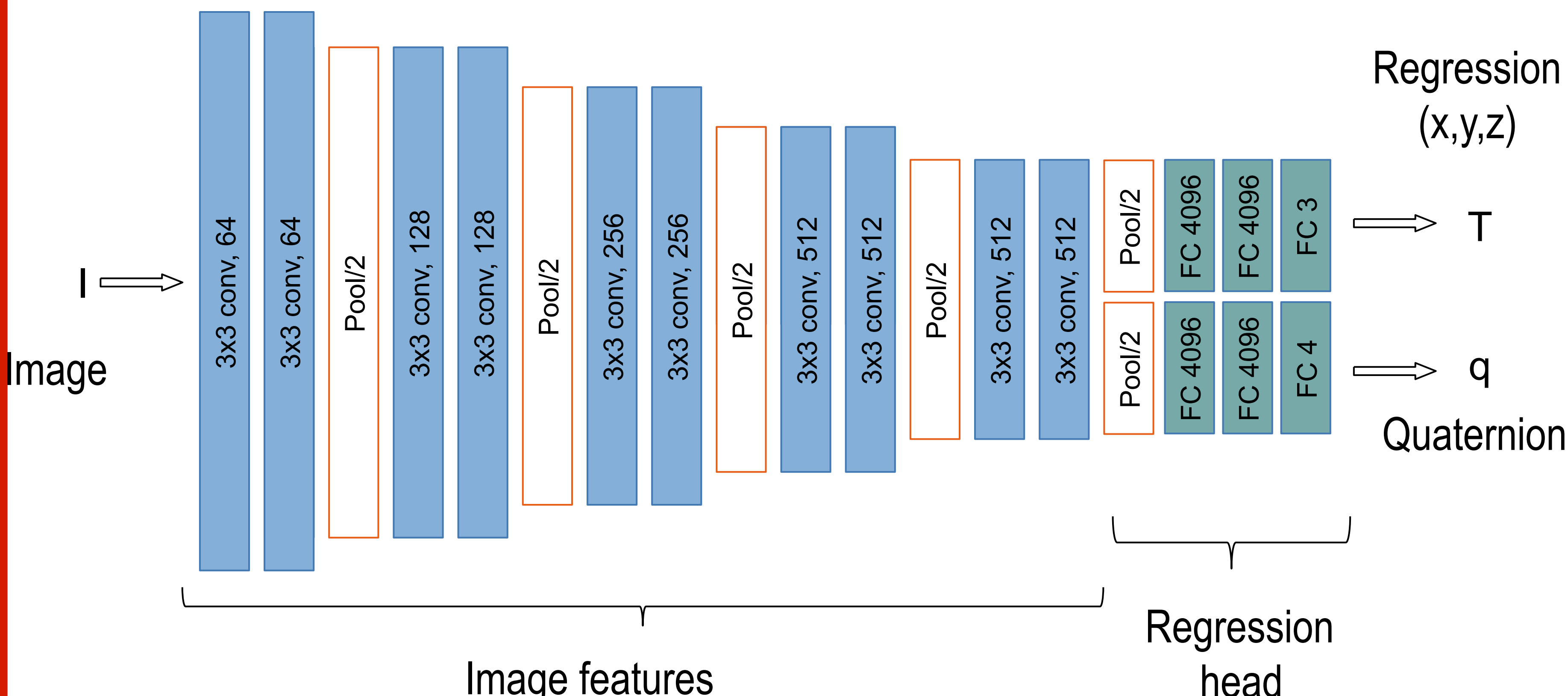
Dataset:

Capturing Images + ground-truth Position

Captured Images

Re-localization using DL

CNN Model:

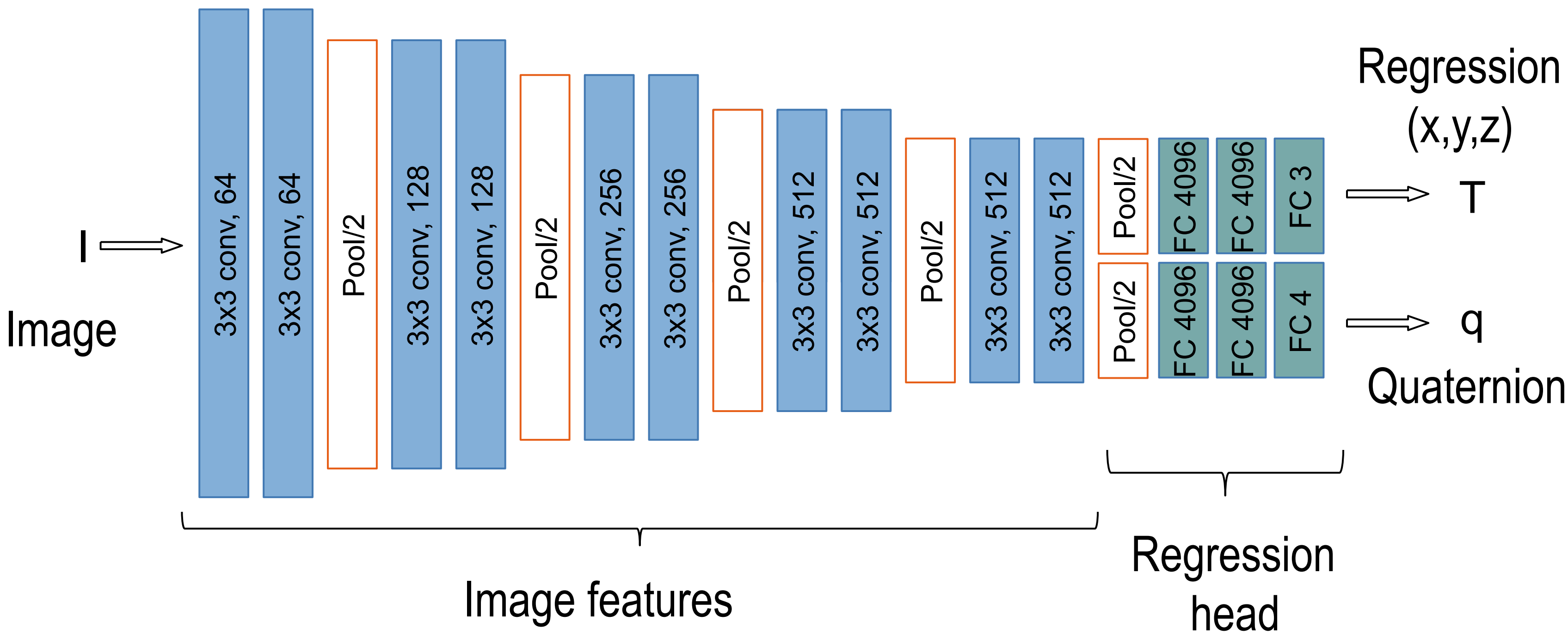


Re-localization using DL

CNN loss function:

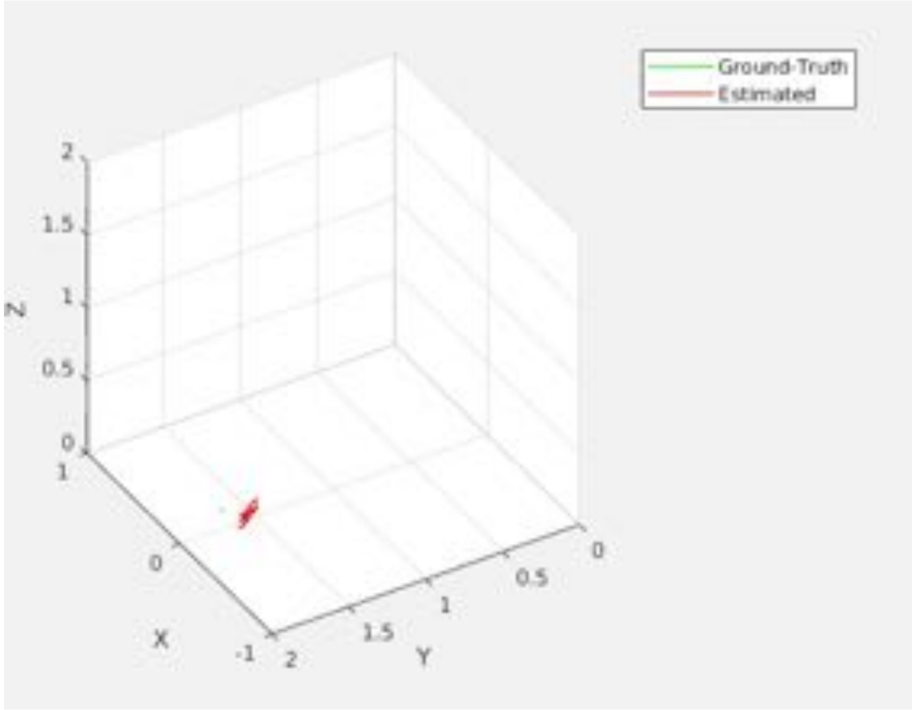
$$\mathcal{L} = \|T^{\star} - T\|_2 + \beta \left\| q^{\star} + \frac{q}{\|q\|} \right\|_2$$

* Ground truth



Re-localization using DL

Dataset results: The estimated L_2 error is 4,8 cm

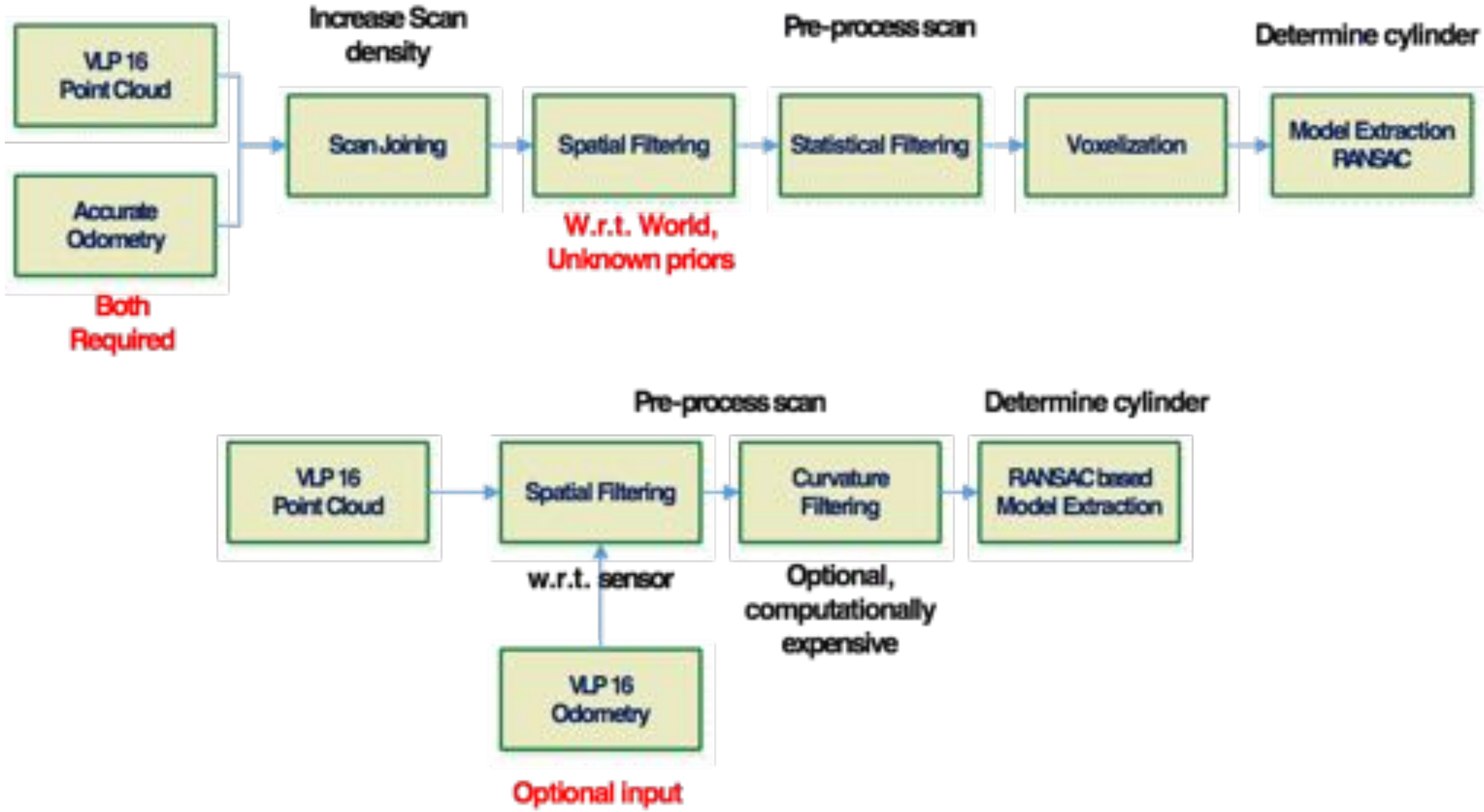


Pose relocalization

Test sequence

Pipe Detection with LIDAR

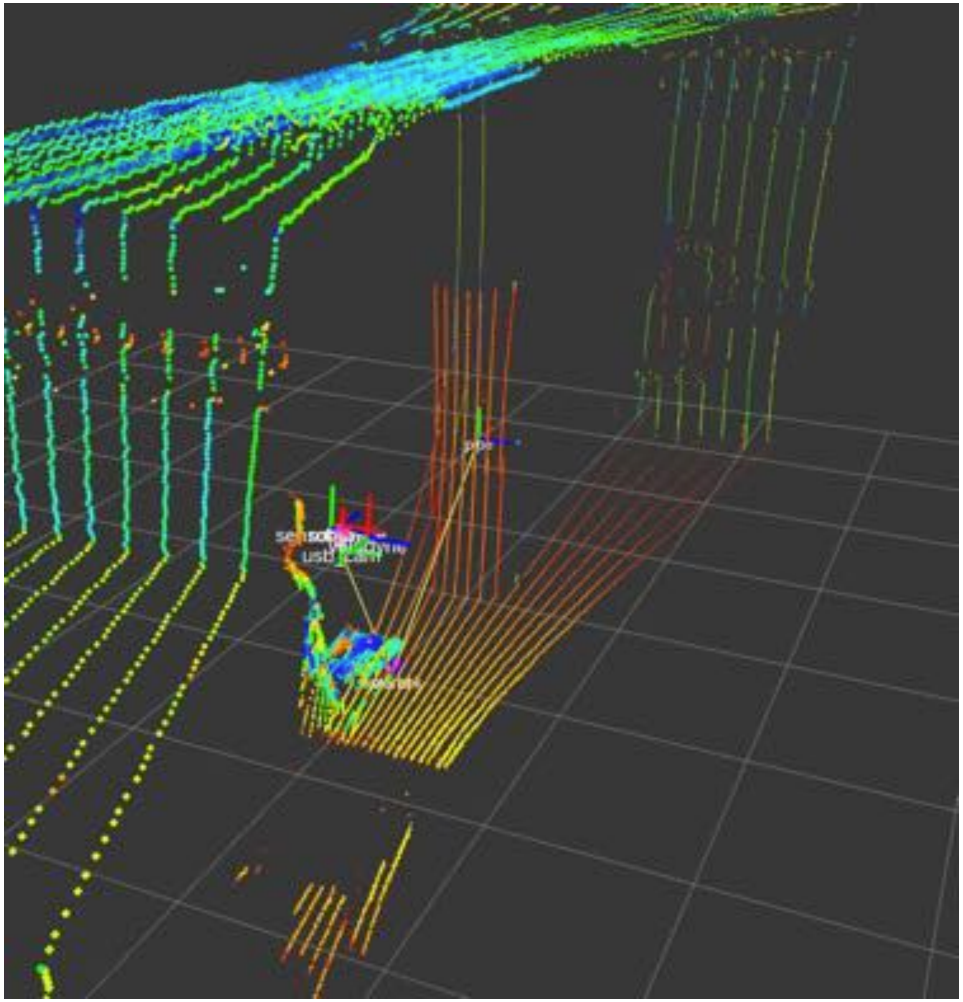
Architectures



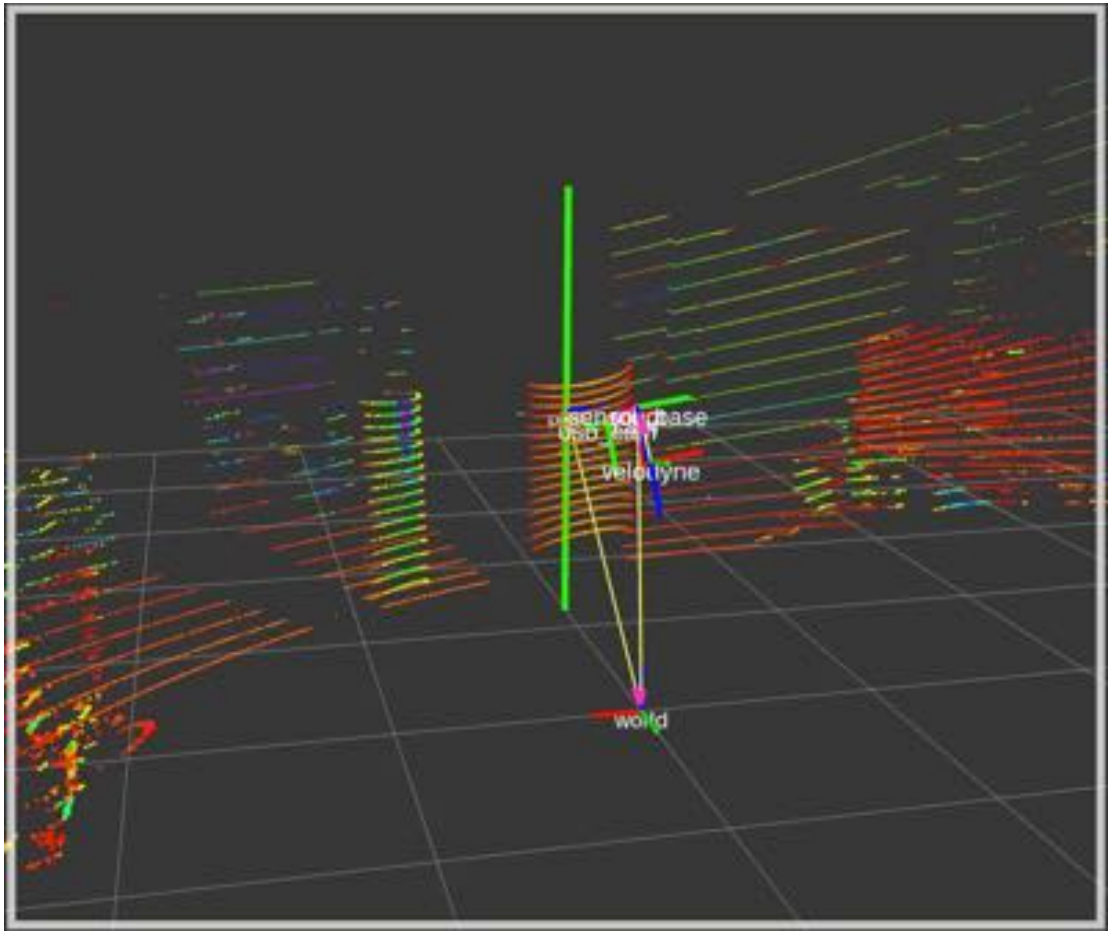
Pipe Detection and Localization

Current Pipeline

- *Reduces pointcloud size asap*
- *Avoids resampling*
- *Avoids dynamic priors:*
  - Odometry not required
- *Minimize "tf" calls:*
  - not required
- *Avoids heavy data sharing between processes*
- *4-fold avg. rate increase*
  - 0.75~1Hz vs 3.5~4.5Hz



Pipe Detection and Localization

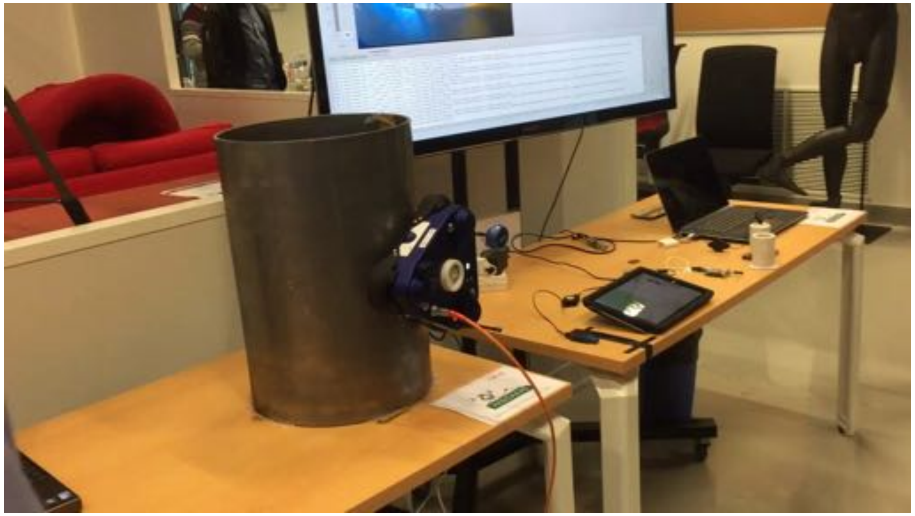


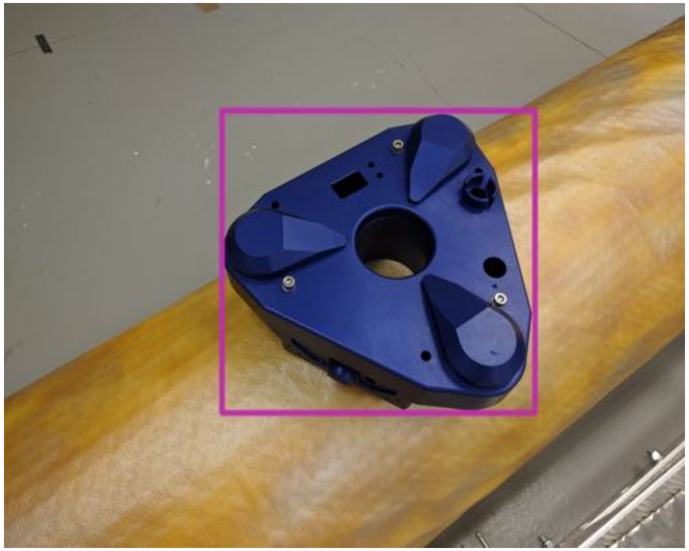
Multiple pipe discrimination

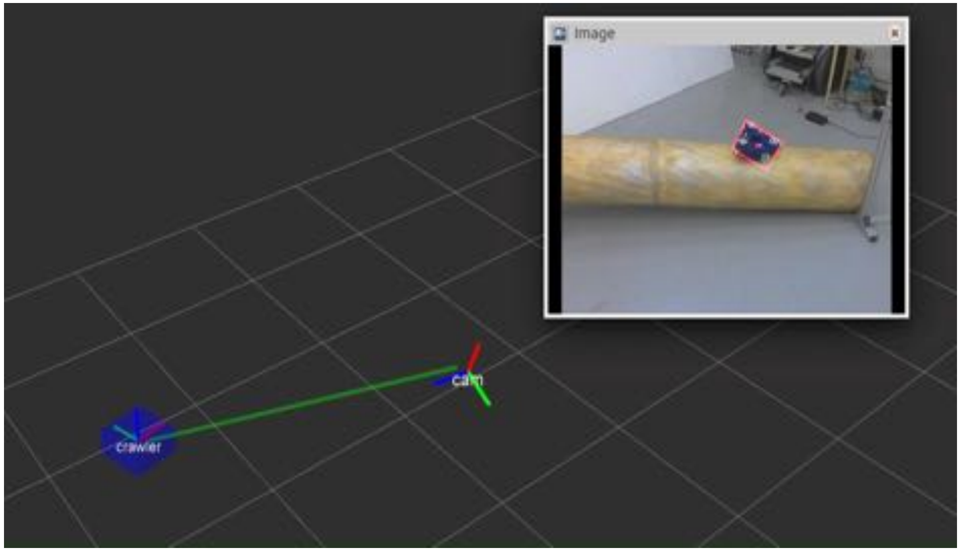
Parallel position

0.35 vs 0.5 m diameter

Crawler Detection and Localization

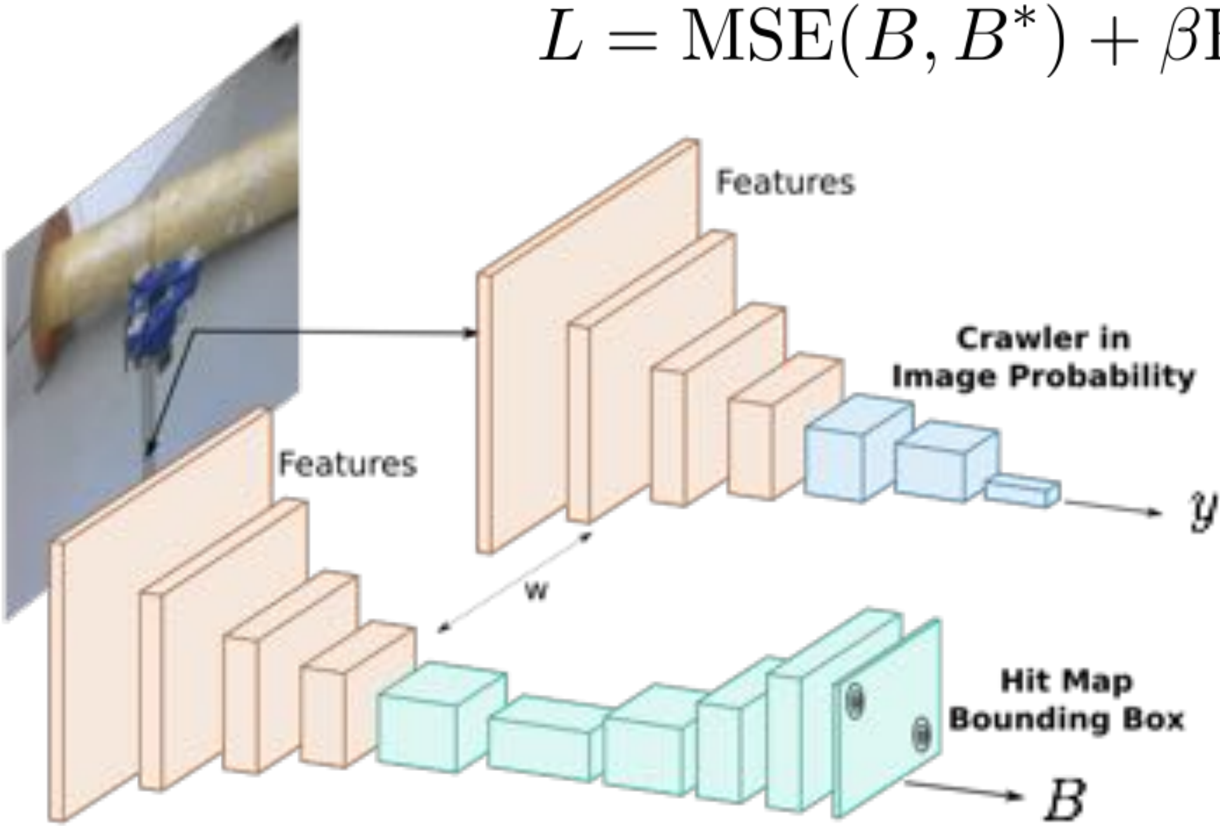






Crawler Detection and Localization using DL

$$L = \text{MSE}(B, B^*) + \beta\text{BCE}(y, y^*)$$

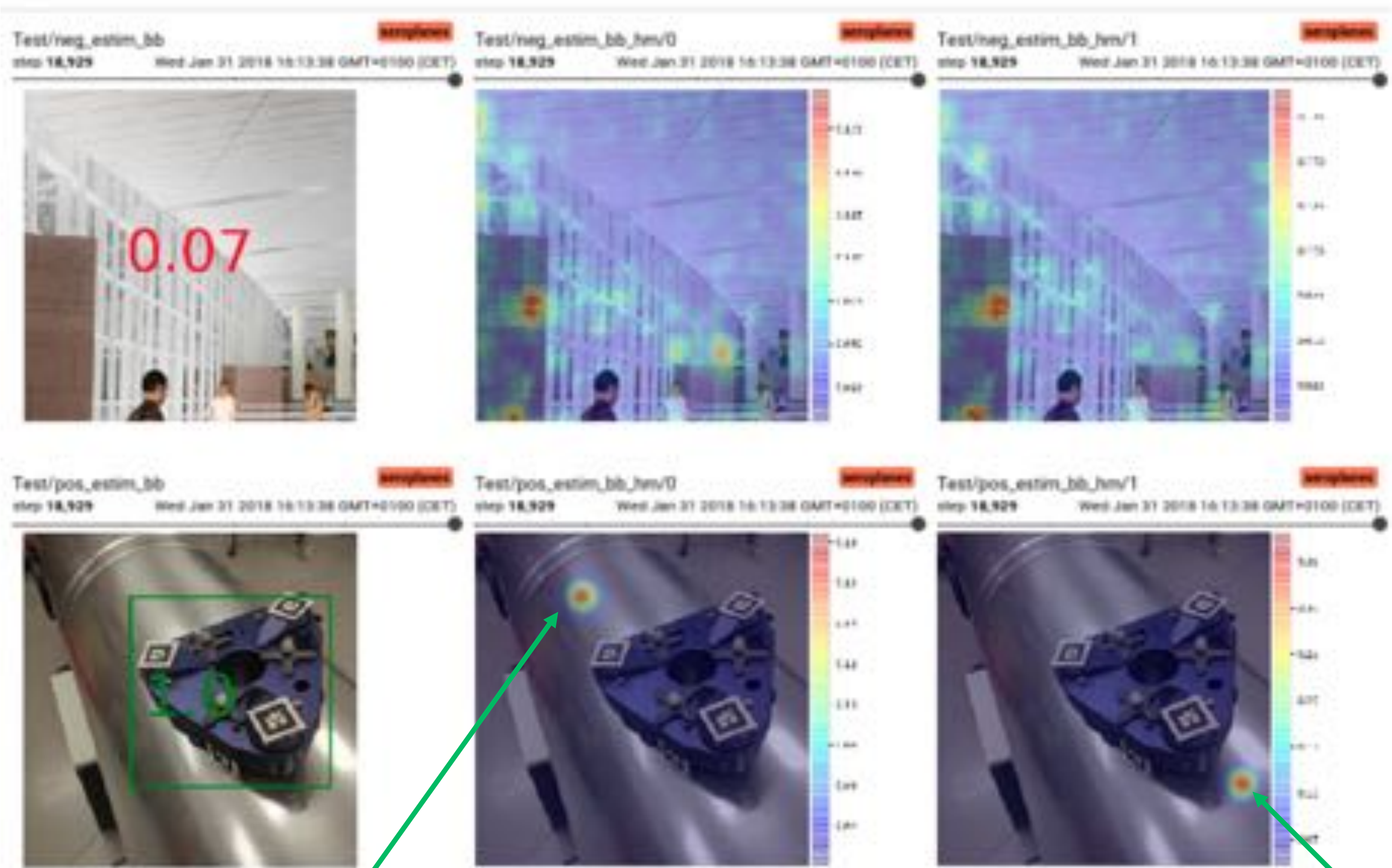


Crawler Detection and Localization using DL

Currently improving the model with a mock dataset of planes detection

Negative match

Positive match

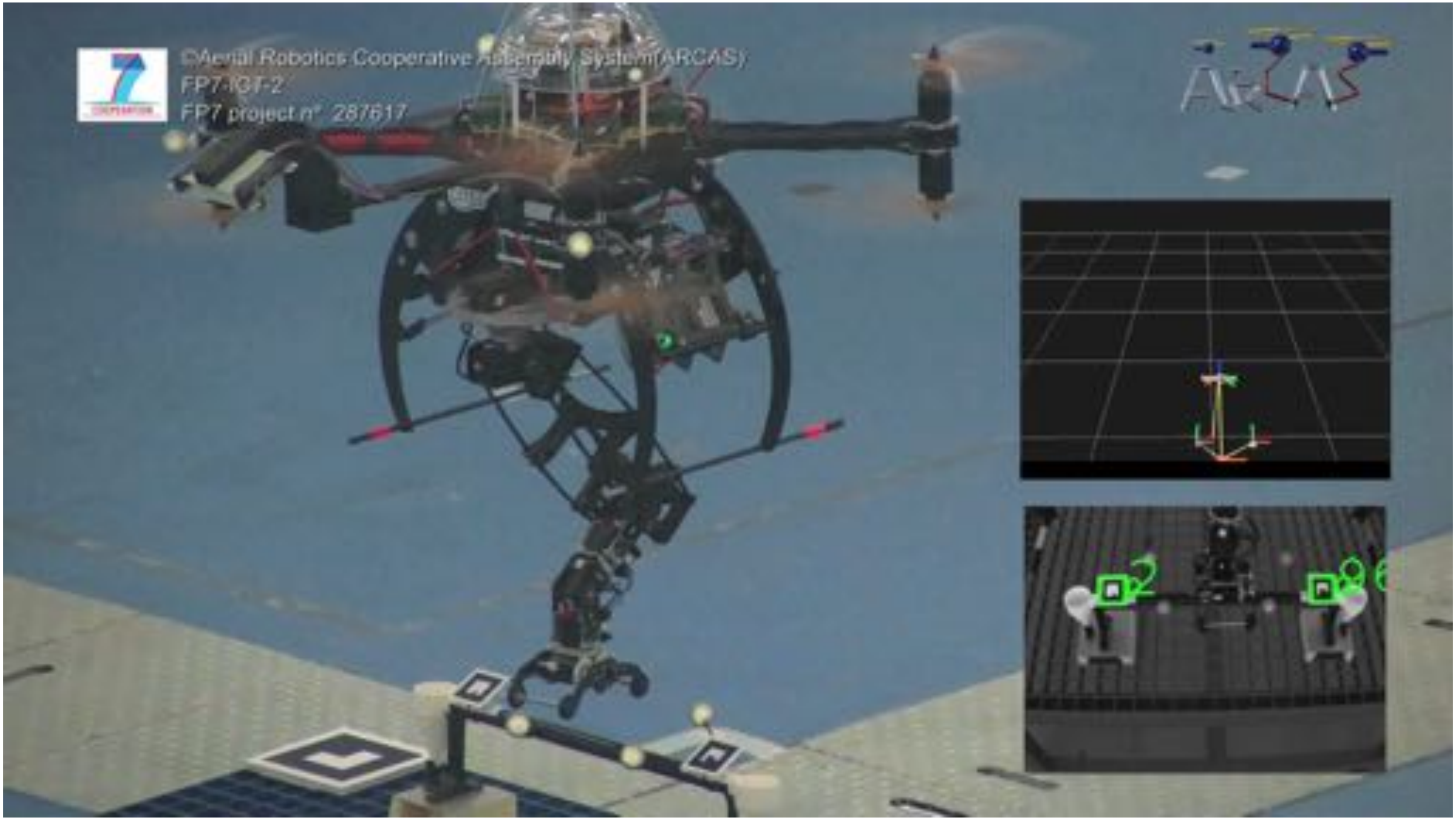


B. Box first corner

Current AP 0.93

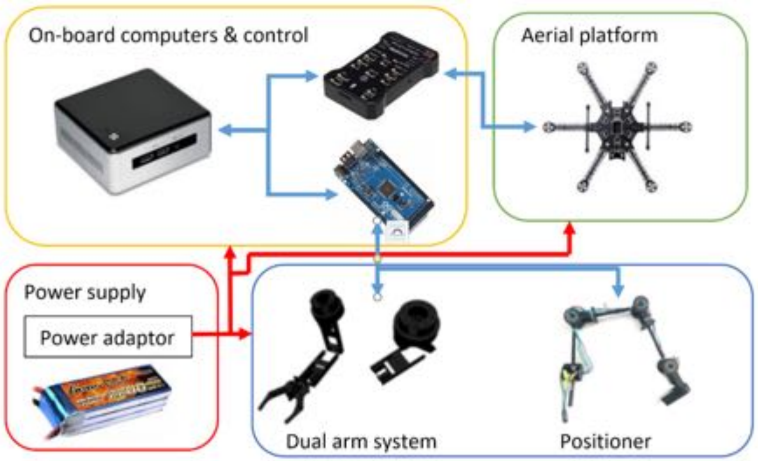
B. Box second corner

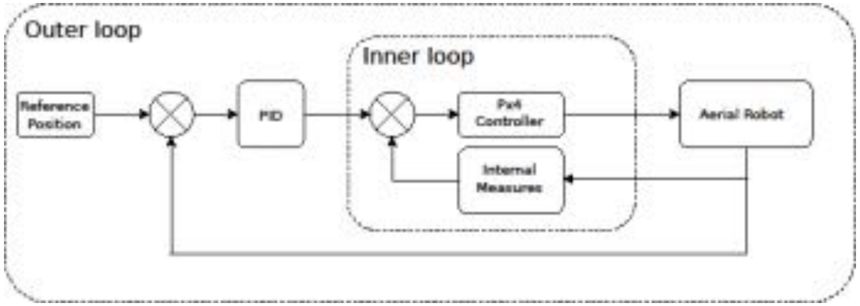
Crawler Grasping: ARCAS Results



Aided Positioning System using Contact Tool

Provided relative position information of the UAV in contact with a surface.





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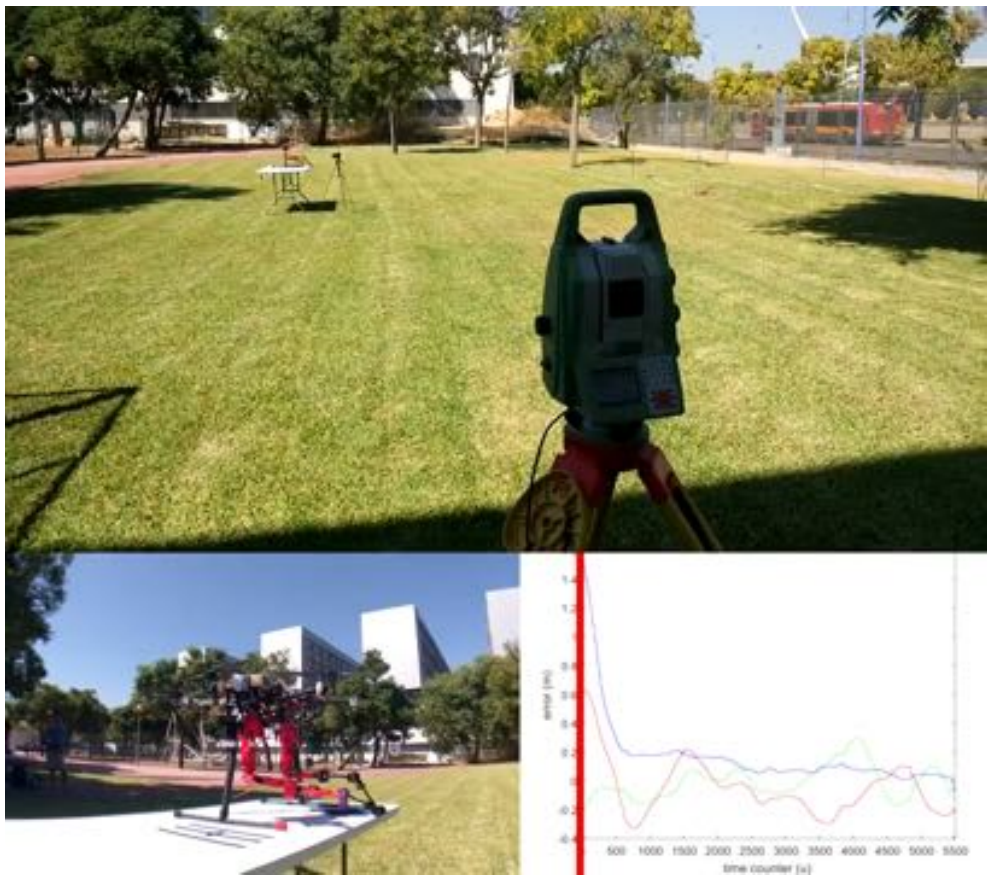
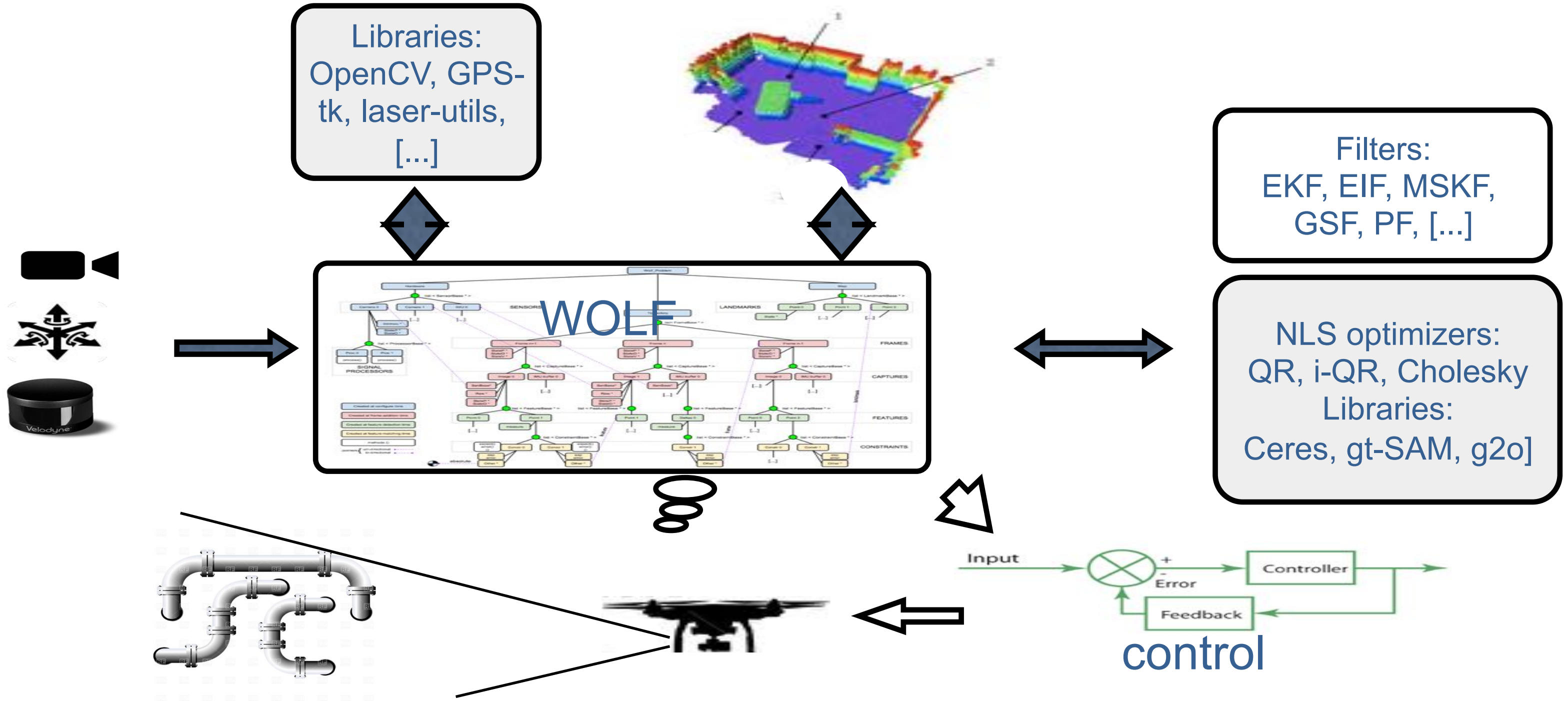
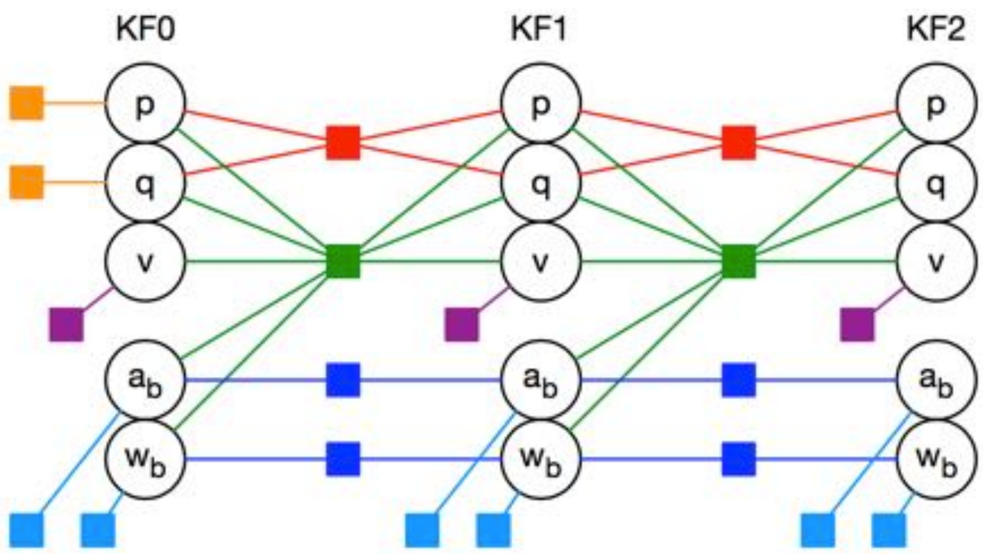


WOLF: A Versatile Framework for Localization and Mapping

Framework to deal with SLAM data management and computations. In a general case, the user has to define and program sensor-related code (observation model with Jacobians)



WOLF: IMU pre-Integration in S3 and SO3



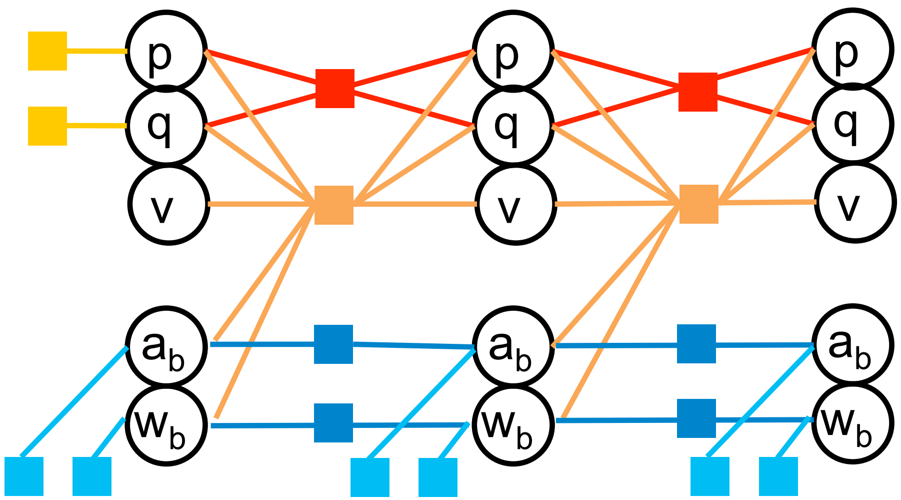
Detailed factor graph for the initial Key Frame (KF) and two steps

p: position
q: orientation (quaternion)
v: velocity
a_b: Accelerometers biases
w_b: Gyros biases

- : Initial pose
- : Leg kinematic factor
- : Zero-velocity factor
- : IMU's delta pre-integration factor
- : Bias drift factor
- : Bias absolute factor

Odometry based on auto-calibrating inertial measurement units attached to the feet. Dinesh Atchuthan, Angel Santamaria-Navarro, Nicolas Mansard, Olivier Stasse and Joan Solà. Accepted at ECC18 (Collaboration LAAS-CSIC)

WOLF: Visual-Inertial Odometry using Multiple View Geometry



p: position
q: orientation (quaternion)
v: velocity
a_b: Accelerometers biases
w_b: Gyros biases

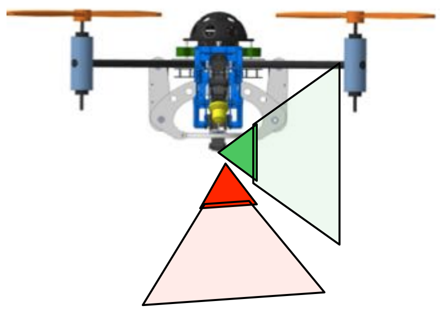
- : Initial pose
- : Visual odometry factor
- : IMU's delta pre-integration factor
- : Bias drift factor
- : Bias absolute factor

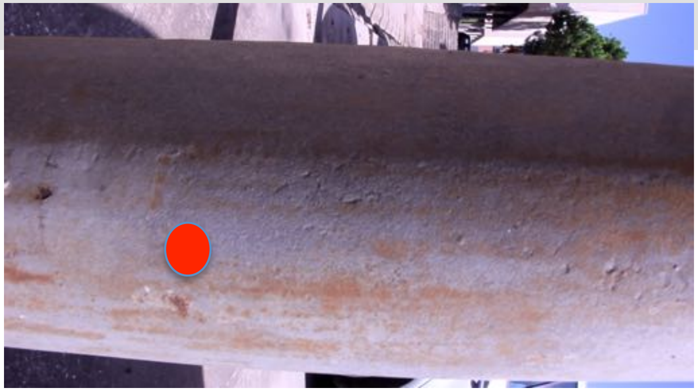
Detailed factor graph for the initial Key Frame (KF) and two steps

Ongoing work:

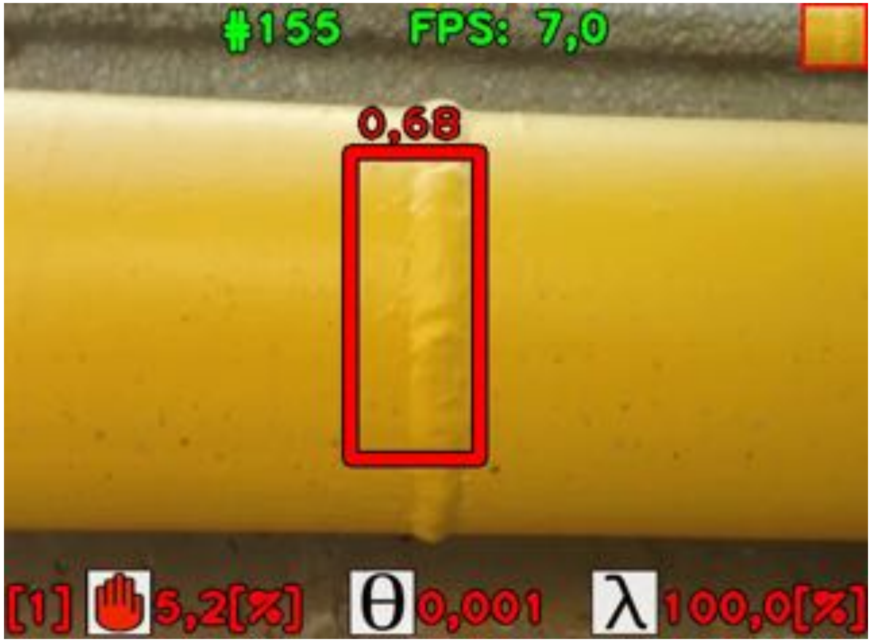
- We combine IMU (delta pre-integration) with a Visual Odometry.
- Visual Odometry based on Trifocal tensor (Epipolar geometry)

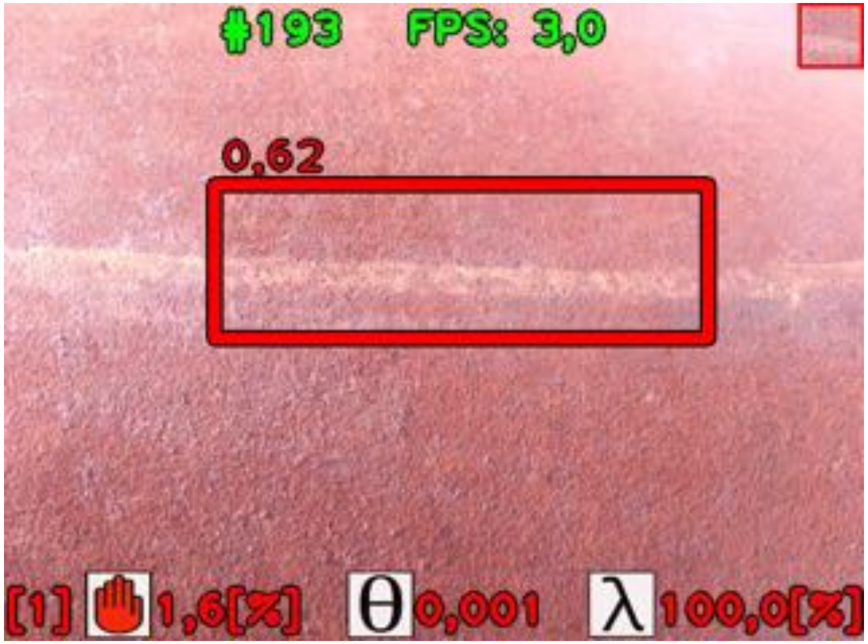
Object / Area Identification





Identify the objects for inspection, manipulation, landing, etc.





Thank you

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