

MSFUSION

Next Generation Motion Sensors for Hybrid GNSS/INS Solutions in high accuracy machine control applications [NAVISP-EL1-042]





- Project Introduction
- HW Design
- SW Design
- Test Campaign Results
- Conclusions and Recommendations

- Sensor data fusion techniques based on GNSS, INS and complementary sensor data for improved position estimates in challenging use cases.
- Benchmark data fusion methods in indoor, outdoor and mixed scenarios.
- Engineering BreadBoard (EBB) with multiple heterogeneous sensors.
- Emphasis on analysing classical and stochastic approaches, with additional focus and investigation of AI / ML techniques.
 - ML in Filters
 - ML applied to vision-based localization
- Architectures and techniques exploiting clusters of multiple low-cost sensors of the same type.
- Stable timing references (Miniaturized Atomic Clocks) for improved PNT availability in case of reduced number of PNT satellites.
- Simulations for data from different sensors and GNSS

■ Applications

- Autonomous cars, robots, ships, railways
- Challenging environments without GNSS coverage, large errors (multipath, low satellite number), intermittent coverage
- Low cost MEMS IMUs

■ Use Cases:

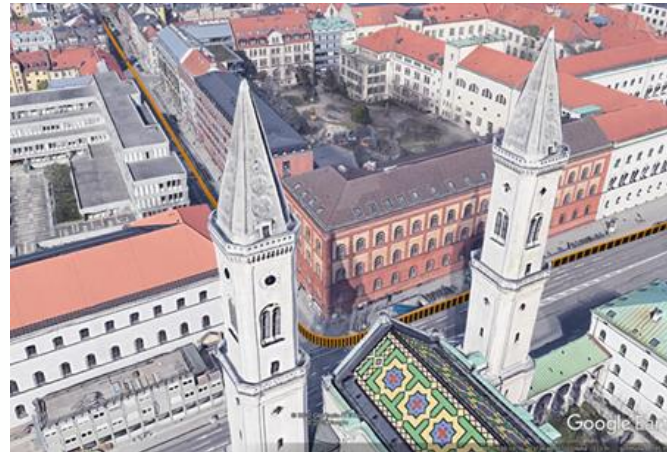
- Pedestrian
- Vehicle

■ Scenarios:

- Urban
- Port
- Mixed indoor
- Partial Outdoor



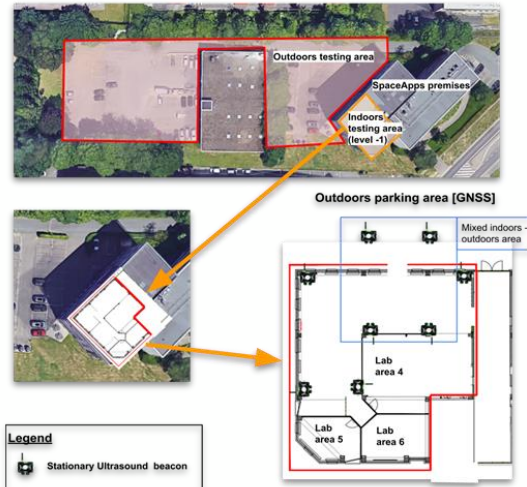
- Applications & Challenges
 - Autonomous cars, robots, transport
 - Challenging environments with limited and partial GNSS coverage (multipath, low satellite number)



- Applications & Challenges
 - Narrow spaces between containers with large amount of metal objects (avg. 3 containers high)
 - Limited and sporadic GNSS coverage
 - Large moving vehicles and trucks in the field of view



- Applications & Challenges
 - Autonomous cars, trucks, industrial area, warehouse
 - No GNSS coverage when indoor
 - Transition between indoor and outdoor
 - Large errors (multipath, low satellite number), intermittent coverage



- Applications & Challenges
 - Industrial setting with partially covered areas for storage of vehicles and goods
 - Partial GNSS signals with dead spots
 - Warehouse optimisation, equipment tracking

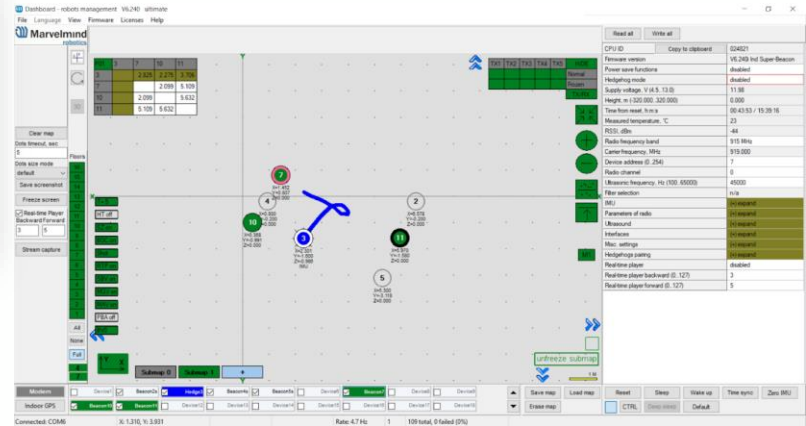


- Open-Sky: RTK + High-Grade IMU (cm-level precision)



Xsens AHRS
MTI-300-2A8G4

- Indoor: Ultra-sound system (4 beacons set-up)



- Use case driven technical analysis
 - Broad range of scenarios
 - Lighting conditions
 - GNSS outage/multi-path
 - Visual and ranging
 - Computation limits

- Cost driven
 - VIMU – new development
 - Wifi RTT
 - Cameras

- Real time – more focus than post processed

- Investigate of ML approaches over classical

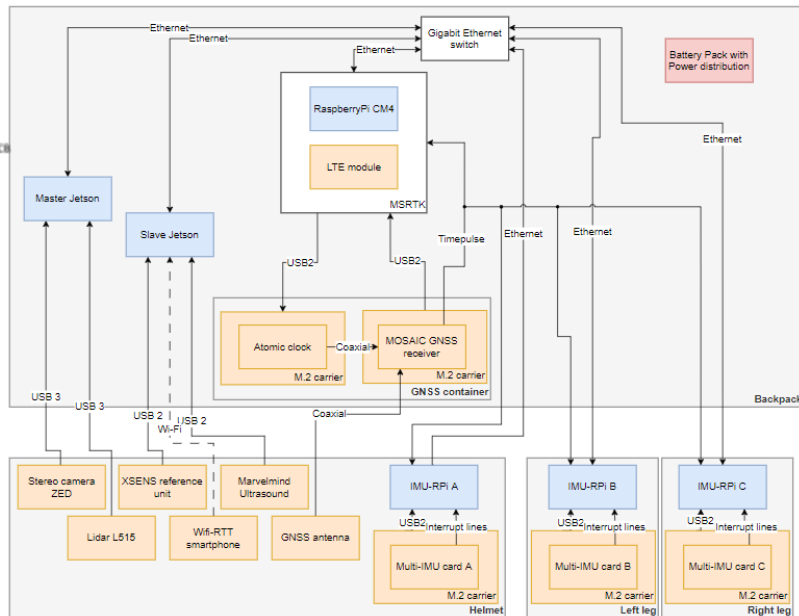
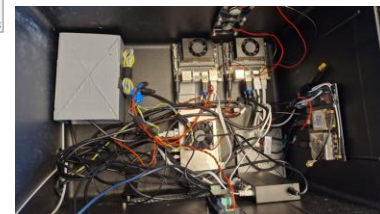
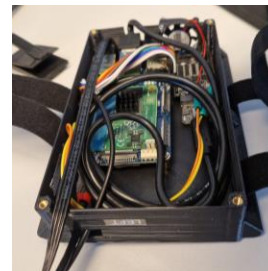


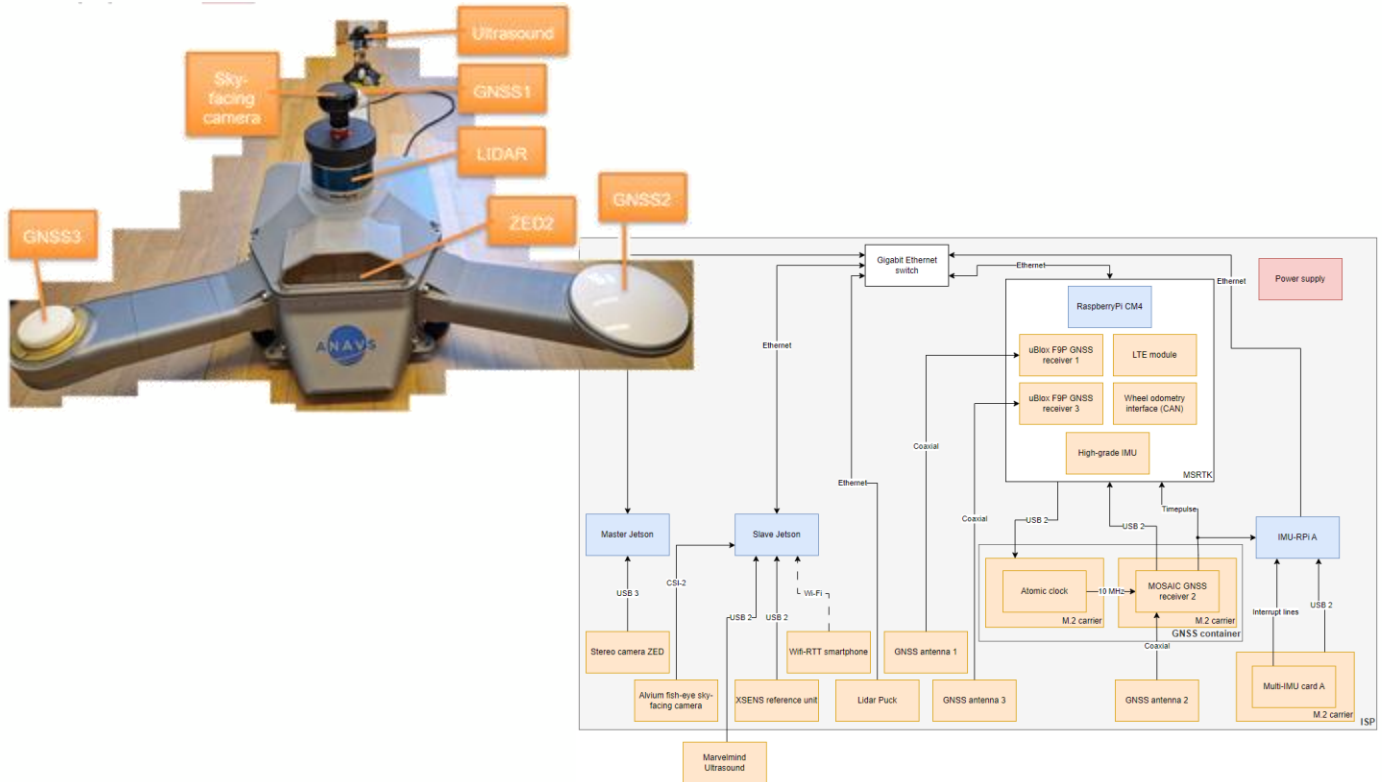
- Project Introduction
- HW Design
- SW Design
- Test Campaign Results
- Conclusions and Recommendations

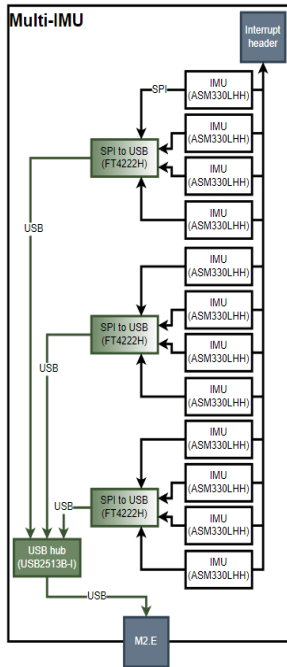
- Jetson Orin NX
 - Octa core processor with 16GB memory
 - 1024 GPU cores operating at 100 TOPs
 - Power rating of 25W
- Zed Stereo camera
 - Low cost
 - High resolution
 - SDK with multiple features
- Velodyne VLP16 (vehicle EBB)
 - Low cost when compared to other 360° LIDARs
 - Dense enough for good feature extraction and sparse enough for real time processing
 - Low power LIDAR sensor
- Intel L515 (pedestrian EBB)
 - Low-weight and low-cost SSL
- Multi-IMU
 - Combined low-cost sensors
 - Benchmark w.r.t. medium / high grade IMUs
- GT
 - Ultrasound – low cost, mobile system, good accuracy

- * GNSS-Antenna
- * Stereo camera ZED
- * Ultrasound Positioning System
- * Solid-State LIDAR LS15
- * Multi-IMU PCB
- * Multi-Sensor RTK/PPP module (AS9)
- * Jetson Xavier NX
- * Power-Source

Backpack size driven by the battery (room for improvement)







- Multi-IMU (STM-ASM330)

- Helmet

- Backpack

- Foot-IMUs

- M2 to USB-C Adapter

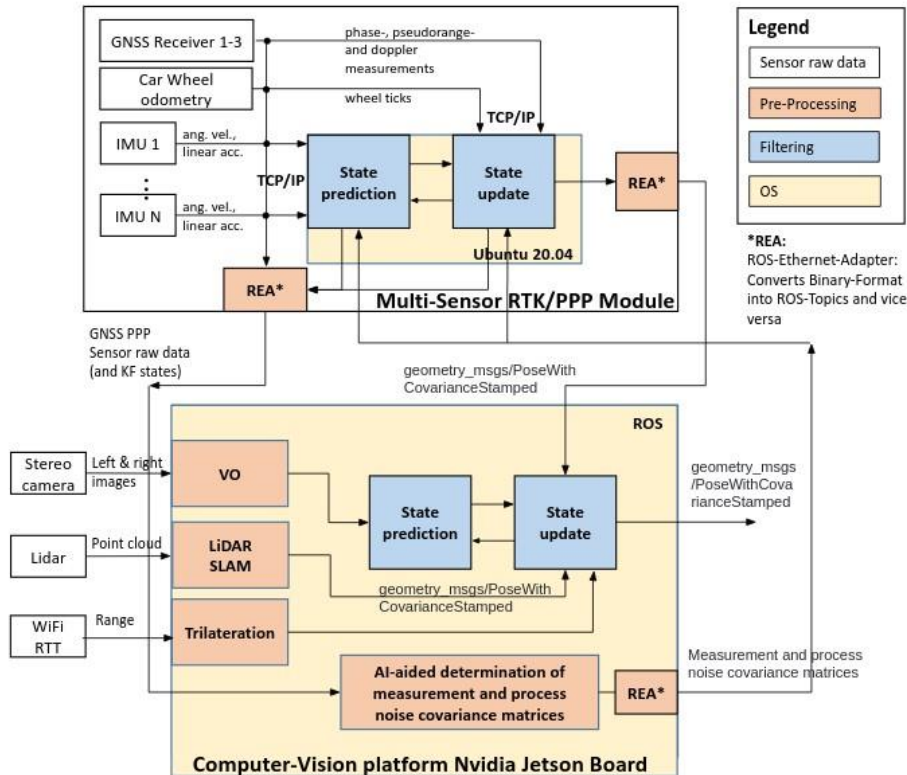
- Atomic Clock and MOSAIC-T M2 Card

- Atomic clock is useful when indoors over a long time to reduce timing drift
- NTP time sync could also be done but lower precision than atomic clock and needs a local/internet server

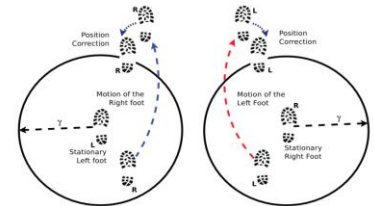
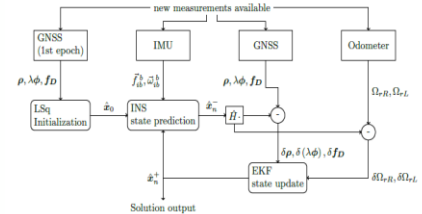




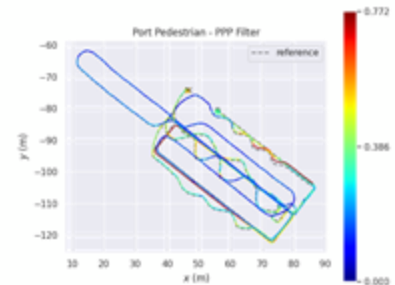
- Project Introduction
- HW Design
- SW Design
- Test Campaign Results
- Conclusions and Recommendations



- Tightly Coupled EKF filter (GNSS PPP, multi-IMU and Odometer)
- Vehicle EBB: Attitude determination with the 2 baselines spanned by the 3 GNSS antennas
- Pedestrian EBB. 1D setup. Feet IMU filter
 - Zero-velocity detector to identify the steps
 - Spatial constraint (feet distance within a sphere of pre-defined radius) to minimise the drift
 - Velocity of the left foot fused with PPP filter to reduce drift during GNSS outages

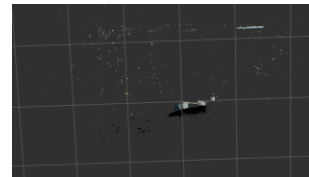
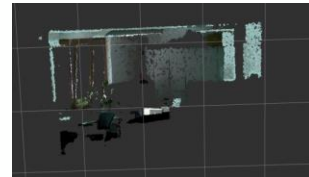
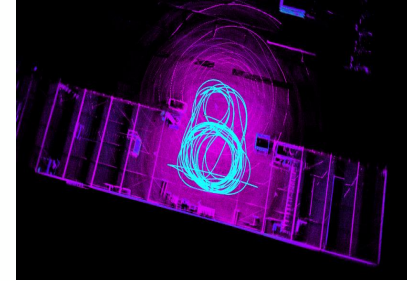


[Source: Prateek G V, et al., Data Fusion of Dual Foot-Mounted INS to Reduce the Systematic Heading Drift]

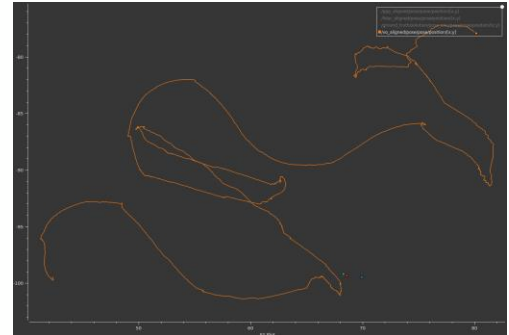
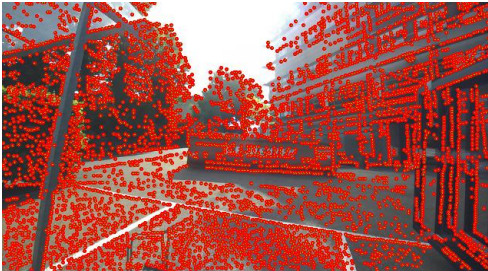


- Vehicle EBB
 - Sensor: VLP16 (mechanical)
 - Point Lio Algorithm
 - Tightly coupled lidar inertial approach
 - Point by point LiDAR feature extraction with state update computation
 - LiDAR state update fused with inertial state update to compute high frequency odometry
 - ikd-Tree for map point insertion/deletion to make the algorithm lightweight.
 - Adaptive voxel parameter tuning for indoor outdoor transitions
 - Adaptive IMU noise parameter tuning to fit accumulated IMU drift.
 - Distortion model to cater to high-speed motions

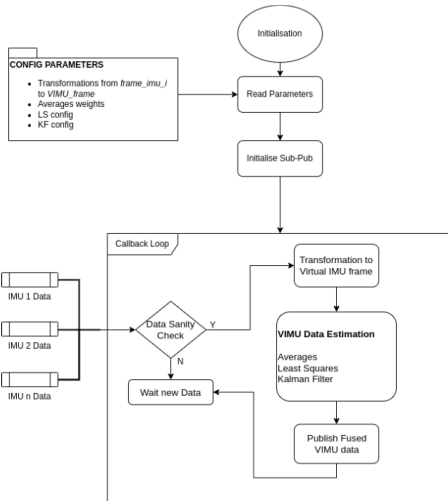
- Pedestrian EBB:
 - Sensor: Intel L515 (SSL) – useless under ambient light conditions
 - **Note:** VLP16 was large/heavy to mount on head
 - Fast Lio Algorithm



- Sensors:
 - Zed2 Camera
 - Zed2 internal IMU
- Visual Localisation track:
 - Full ML algorithm prototyped -> Non-acceptable performance
 - ML combined with classical CV prototyped -> No features tracked
 - MSCKF was tested -> Unstable due to calibration issues
 - ZED package -> Stable solution with minor relative drifts



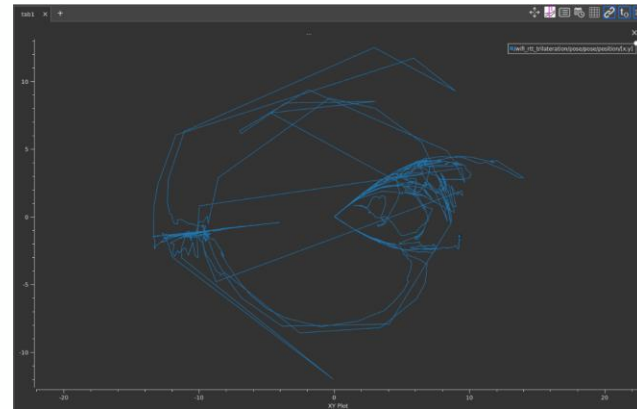
- Fusing the measurements of N imus into one:
 - Three fusing techniques implemented:
 - Averages
 - Least Squares
 - Extended Kalman Filter
- It offers an improved estimation (reduced error metrics compared to a high-grade IMU), redundancy and robustness

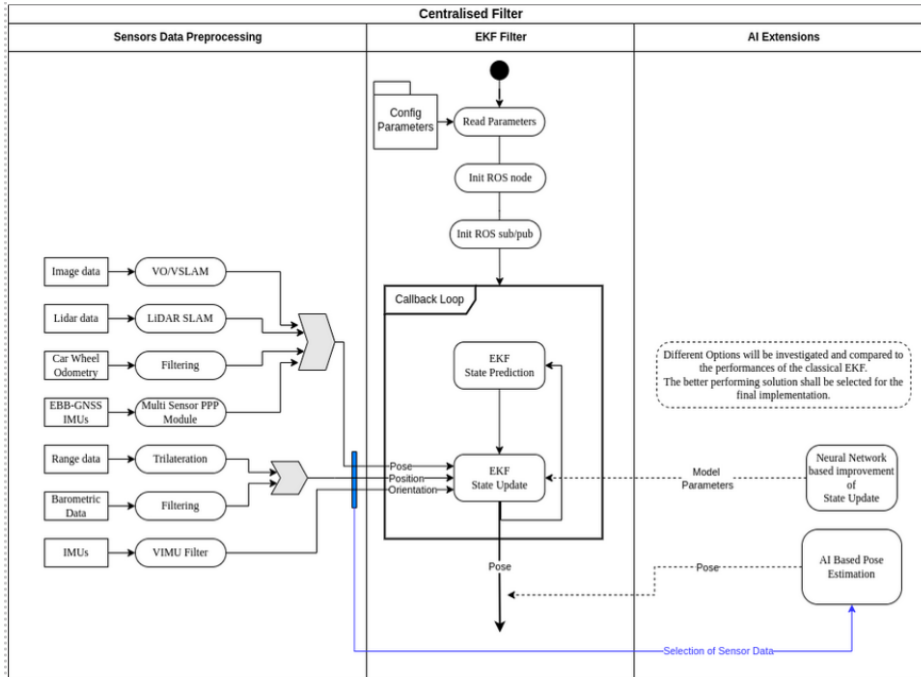


RMSE	VIMU EKF	VIMU Least Squares	VIMU Average	Best IMU	Worst IMU
Angular Velocities	0.309	0.125	0.346	0.332	0.342
Linear Acceleration	1.177	0.881	1.23	1.163	1.264

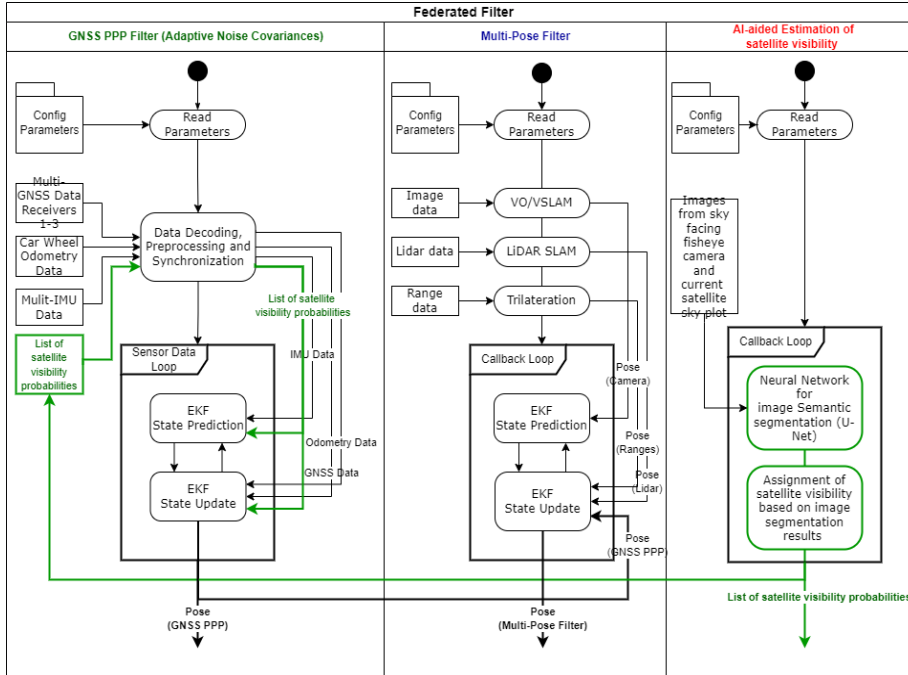
Comparison between RMSE of 3 VIMU methods and Best and Worst IMUs of the group of 10 (benchmarked against a XSens MTi 300) in the Vehicle EBB.

- Set Up:
 - 4 Static Access Points
 - 1 Mobile-phone to track the position
- Algorithm:
 - Signal trilateration -> Mobile2AP distance based
- Issues:
 - Not stable -> Jumps of meters
 - Clustered regions (in and out)





- Prediction step :
VIMU Update step:
PPP+IMU, Lidar, RTT, and VO.
- In the update, the AI extension KalmanNet was introduced.
- The classical EKF model and KalmanNet model were assessed across all scenarios.
- EKF model demonstrating consistent performance was chosen.

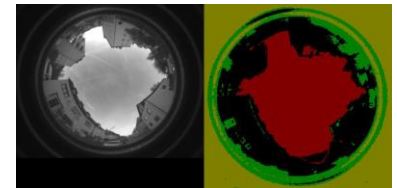


Loosely Coupled EKF Filter

Lidar fusion method

- Absolute (drift - ↑uncertainty)
- Relative (stochastic cloning approach)

Fisheye visibility information used to underweight non direct LOS measurements





- Project Introduction
- HW Design
- SW Design
- Test Campaign Results
- Conclusions and Recommendations

Urban

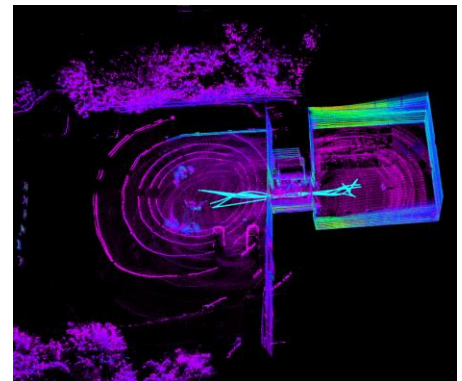
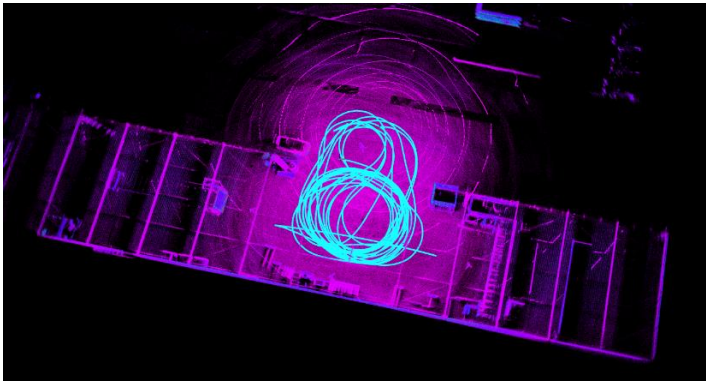
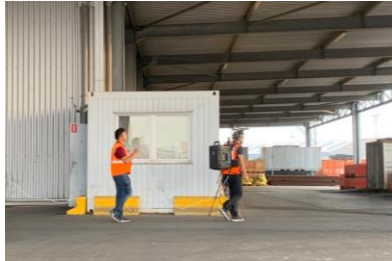


Port

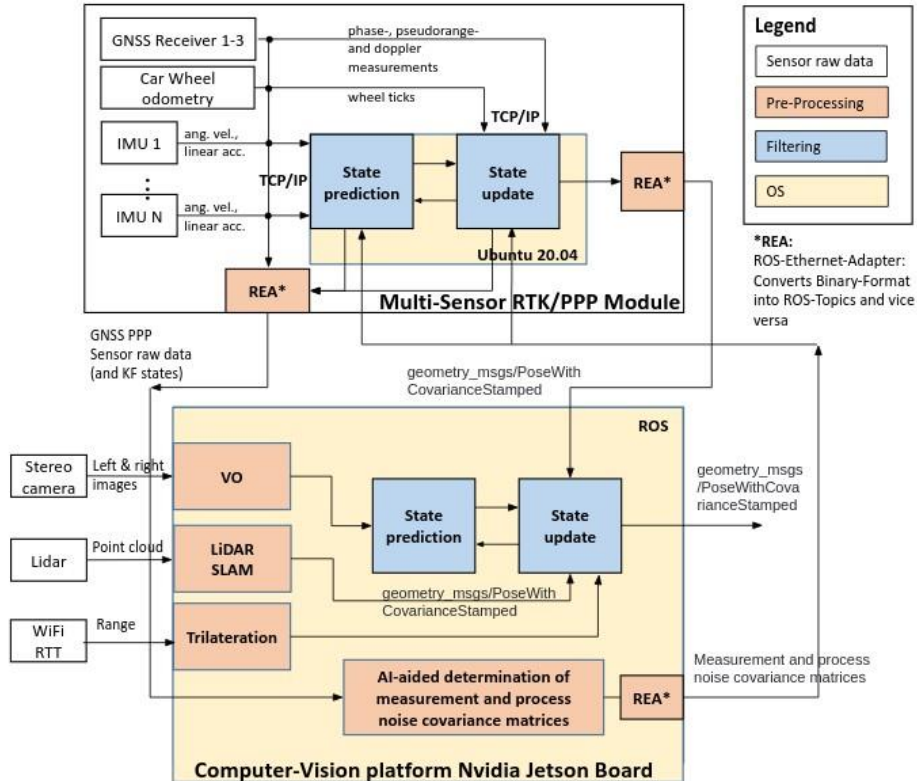


Light-Indoor

Mixed



Global Software Architecture (Recap)

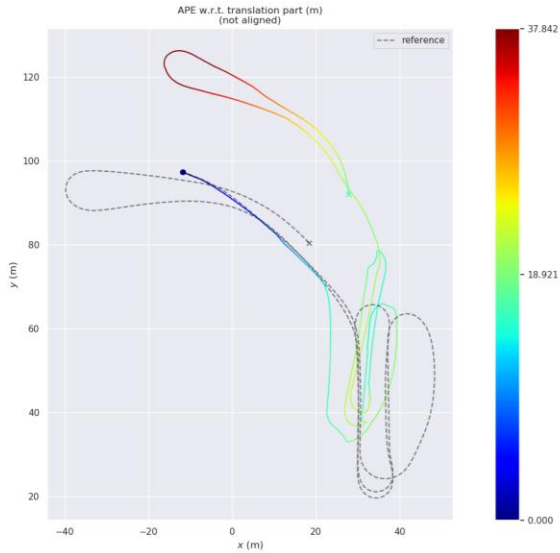


Which subset of results are we showing next

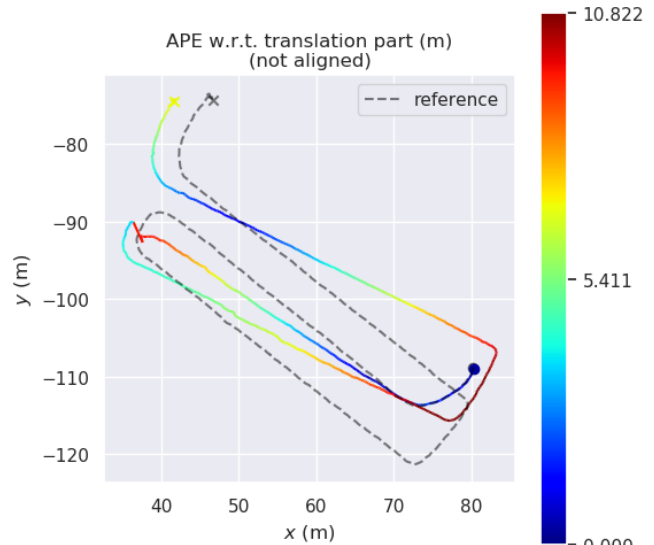


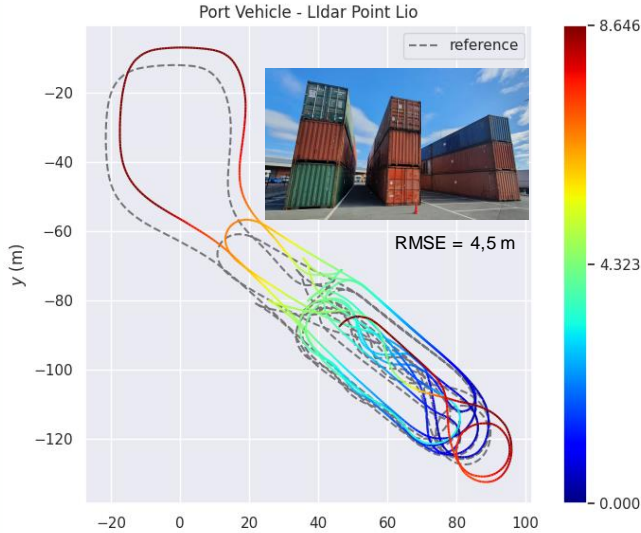
- Results Focus on Port Scenario – has characteristics of outdoor, mixed and partial indoor scenarios
- Results:
 - Individual Algorithm performance
 - Central fusion output performance
- For both EBBs
 - Human
 - Vehicle

Vehicle EBB



Pedestrian EBB

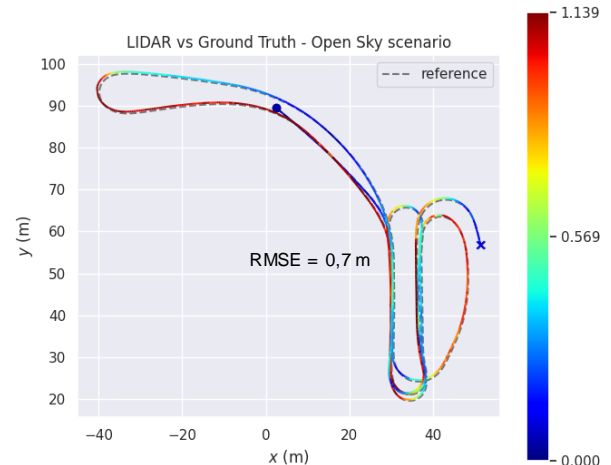




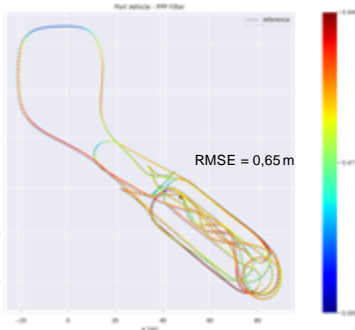
Lidar-algorithm follows very well the reference path

Drift starts when the car drives between containers (planar surfaces with no defined features available).

Excellent results achieved in a port less-challenging conditions (single level containers and more diverse environment)



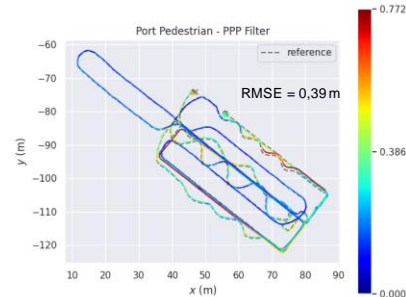
Vehicle EBB



High-accurate results even in very low visibility conditions (GNSS signals occluded by the containers)

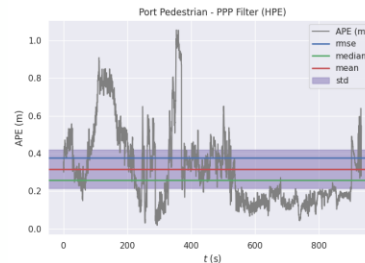


Pedestrian EBB

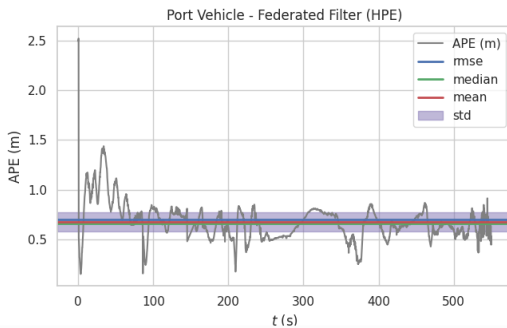
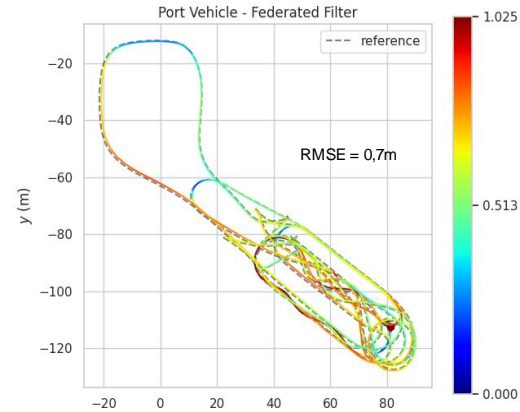


<20 cm horizontal accuracy in open-sky conditions

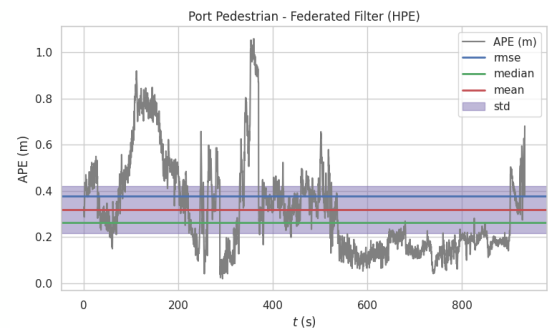
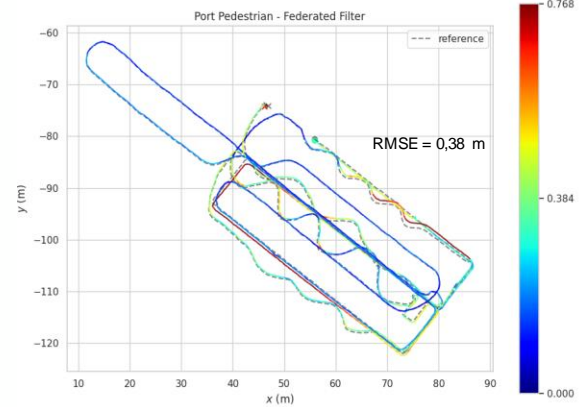
Sub-meter level accuracy when walking through the containers with degraded geometries



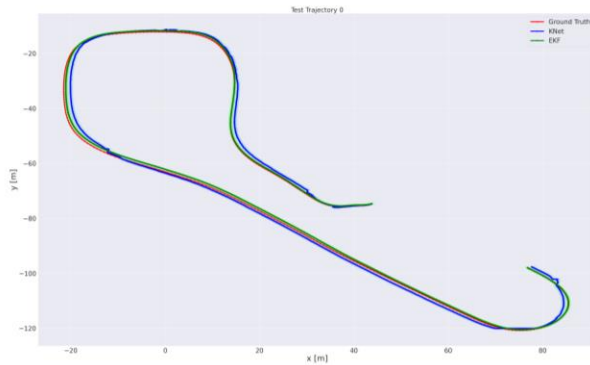
Vehicle EBB



Pedestrian EBB



Vehicle EBB



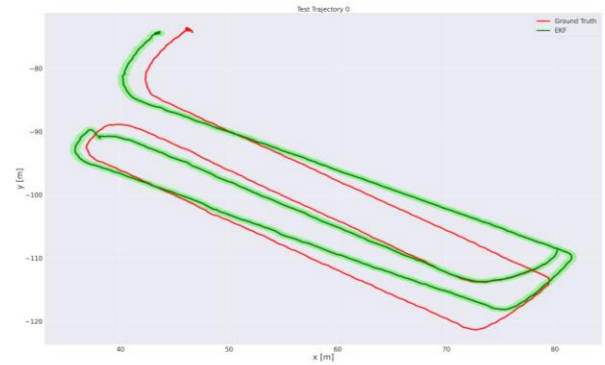
MSE [dB]: -2.697

RMSE: 0.733

x [m]: 0.357

y [m]: 0.540

Pedestrian EBB



MSE [dB]: -0.613

RMSE: 0.932

x [m]: 0.334

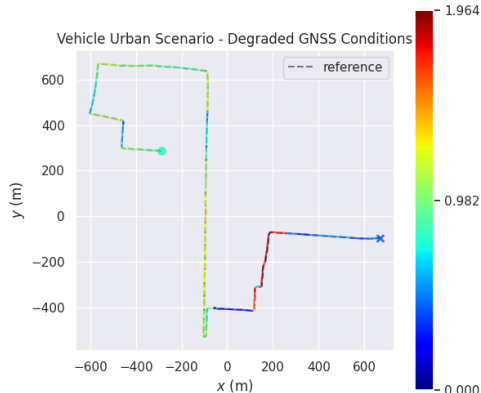
y [m]: 0.686

Consolidated Vehicle EBB Results for 3x scenarios



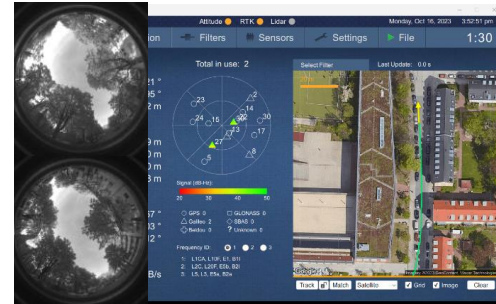
- Previous Slides – provided detailed results of Vehicle & Pedestrian EBB in Port scenario

- Consolidated results of EBBs for other 3 scenarios in the next slides
 - Urban
 - Mixed
 - Partial-indoor

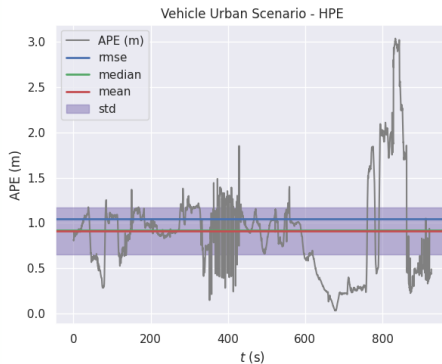


- Federated and Central solutions relying mostly on the PPP + IMU filter

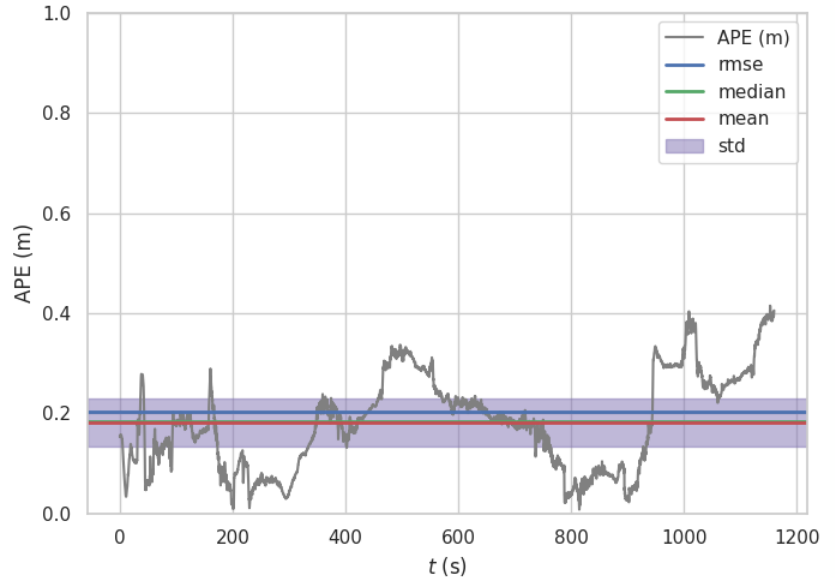
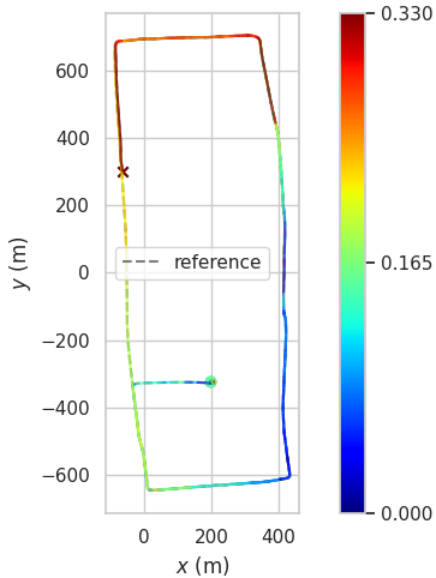
- Low number of satellites in many parts of the track (inc. initialization)

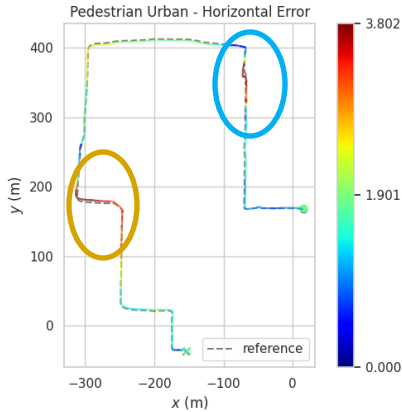


- Signal quality strongly affected by trees and other obstacles, especially in narrow streets
- Dynamical model not perfectly well adapted – tuned.
- Pretty good results obtained in any case, considering the quite challenging environment and signal acquisition conditions.

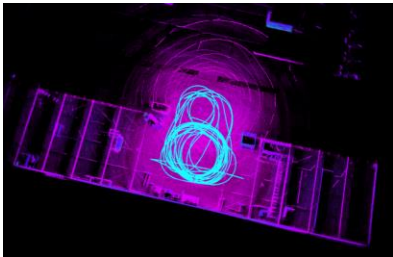
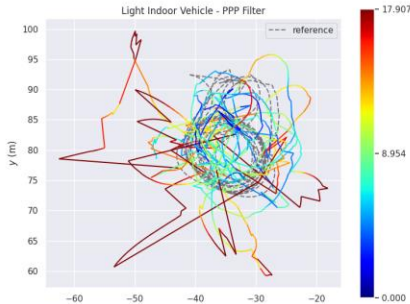


Urban Scenario – Improved Dynamical model





- Sudden drops in the number of valid satellites leading to high position error increase. GNSS degradations driven by **interferences** (multiple sensors and electronic equipment packed in a small area) and **environment conditions** (narrow streets with dense foliage)
- Small offsets at curves, mainly caused by noisy measurements, vibrations and dynamic effects (camera, IMU, antenna attached to helmet).
- Foot-IMU algorithms helps mitigating the solution drift during GNSS degraded situations.
- Velocity of the Foot-IMU filter is only fused when the standard deviation of the PPP position falls below a certain threshold.



(*) Reference trajectory: RTK for outdoor areas and ultrasound indoor.

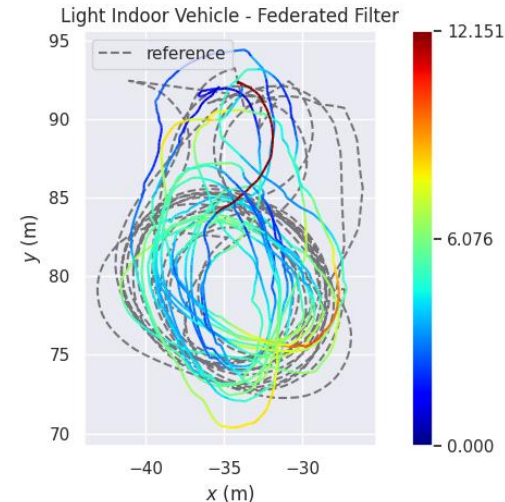
Very complex scenario from the **GNSS** point of view, with continuous transitions from outdoor, semi-outdoor (poor geometry) and indoor conditions.

Excellent **LIDAR** results.

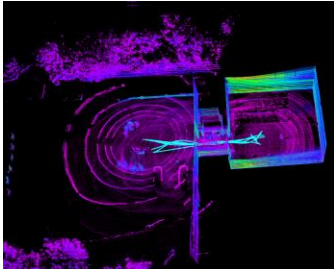
Visual odometry captures the loops and the trajectory pattern but accumulates a large amount of drift over-time.

Mitigated in the federated filter - visual odometry velocity used for prediction purposes

Clear improvement shown in the **Federated Filter** performance (w.r.t. the PPP+IMU solution) thanks to visual and lidar-based information.



Lidar

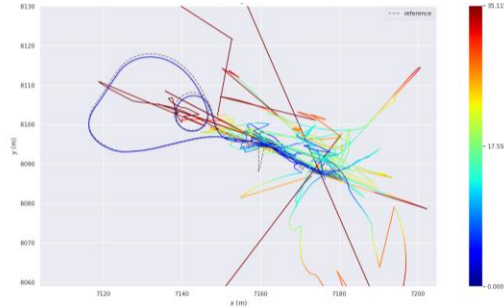


Indoor to outdoor transition and vice versa

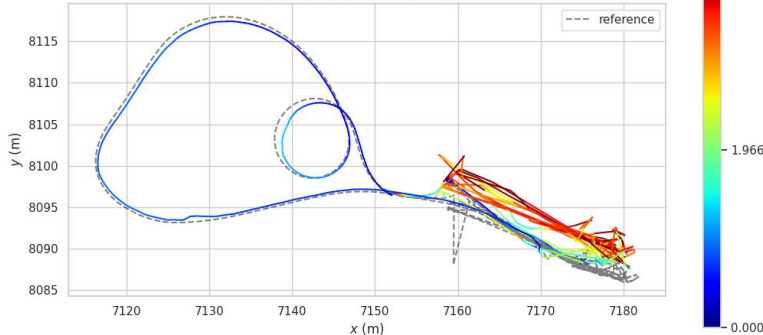
Interesting scenario from lidar and visual-based algorithms, with a very **narrow corridor** driving forward and backward

Very challenging though for both GNSS and IMU sensors

PPP + IMU Filter



Mixed Vehicle - Federated Filter

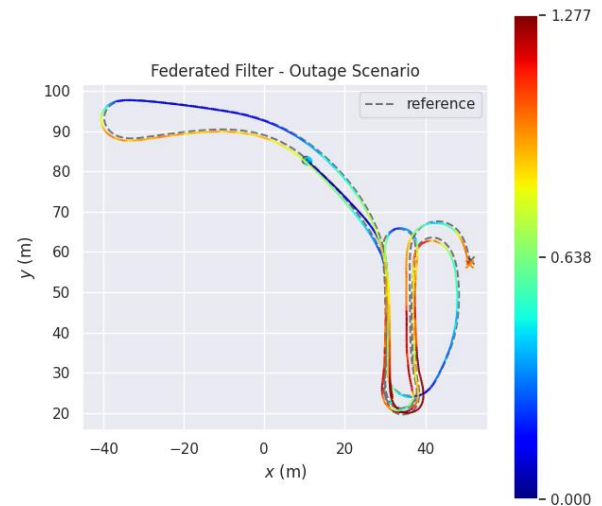
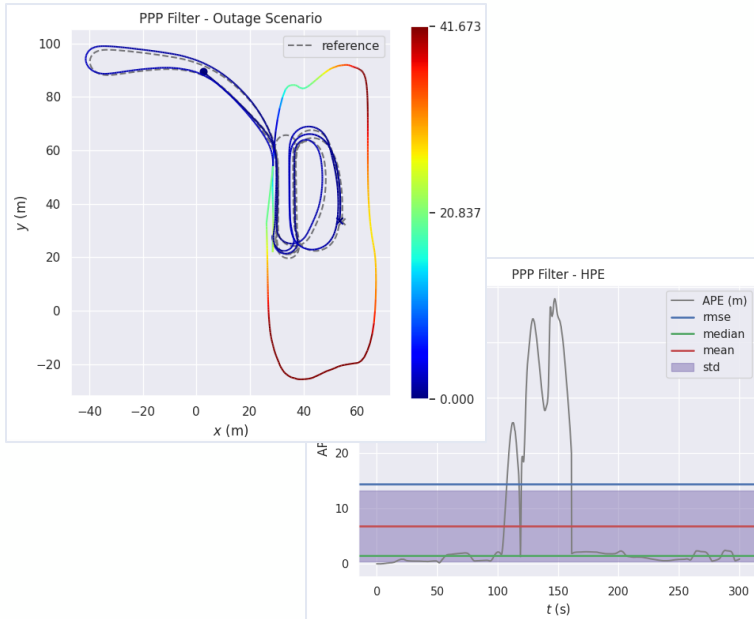


Federated and central filter, thanks to the visual odometry (prediction step) and lidar poses (update step), perform quite well, considering the very challenging conditions, keeping good track of the reference trajectory and providing a **smooth transition** between **indoor** and **outdoor** conditions.

Port Scenario – Federated Filter – With GNSS 60s Outage



- Performance driven by the PPP+IMU filter in the port scenario
- Artificial GNSS outage scenario tested to demonstrate the filter robustness

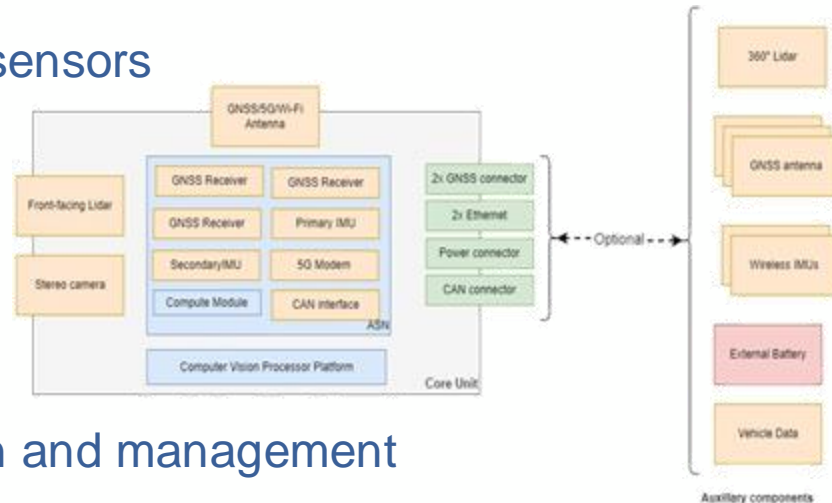




- Project Introduction
- HW Design
- SW Design
- Test Campaign Results
- Conclusions and Recommendations

- PPP + IMU positioning solution achieved reasonably good performance in outdoor Port and Urban conditions across both EBBs
- Lidar solution achieved good results across all the scenarios with the vehicle EBB; Was not good in human EBB due to sensor
- Visual inertial odometry solutions was found to be strongly dependent on the visual features, camera in the environment at a short range to perform consistently.
- Kalman Net based central filter provided solutions across limited scenarios; Classical EKF based central filter performance was good
- Federated Filter achieved good performance across all scenarios
- Computation constraints and complexity in algorithms development, tuning and gathering data using the EBBs was not a trivial
- Reliable fused positioning across all scenarios was satisfactory; scope remains to improve the robustness of visual localization

- Reduce complexity
- Compact and Flexible Architecture
- Core Unit + Optional sensors
- COTS Selection
- ROS2 Framework
- SLAM approaches
- Covariance estimation and management at central filter level
- Improved Dynamical model





BACKUP SLIDES