

RAWSEEDS: Robotics Advancement through Web-publishing of Sensorial and Elaborated Extensive Data Sets

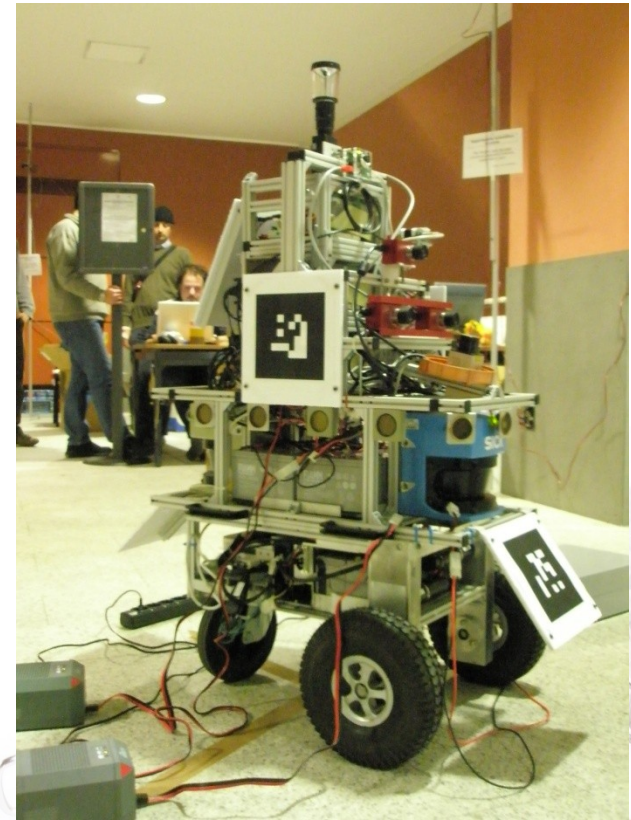


M. Matteucci

RAWSEEDS @ ICAR 2009 – 22nd June 2009 Munich

Today's Special!

- RAWSEEDS in a Nutshell
 - Project Introduction and Aims
- Project activities and results
 - Dataset Collection
 - Dataset Validation
 - Benchmark Problems
 - Benchmark Solutions
- What a future for RAWSEEDS?



What is RAWSEEDS ?

- EU Funded Project in the VI Frame Program from the 1st of November 2006 to July 2009
- A ***Specific Support Action*** to collect and publish a benchmarking toolkit for (S)LAM research
- Involved Institutions:
 - Politecnico di Milano (Italy – Coordinator)
 - Università di Milano-Bicocca (Italy – Partner)
 - University of Freiburg (Germany – Partner)
 - Universidad de Zaragoza (Spain – Partner)



Benchmarking Beyond Radish



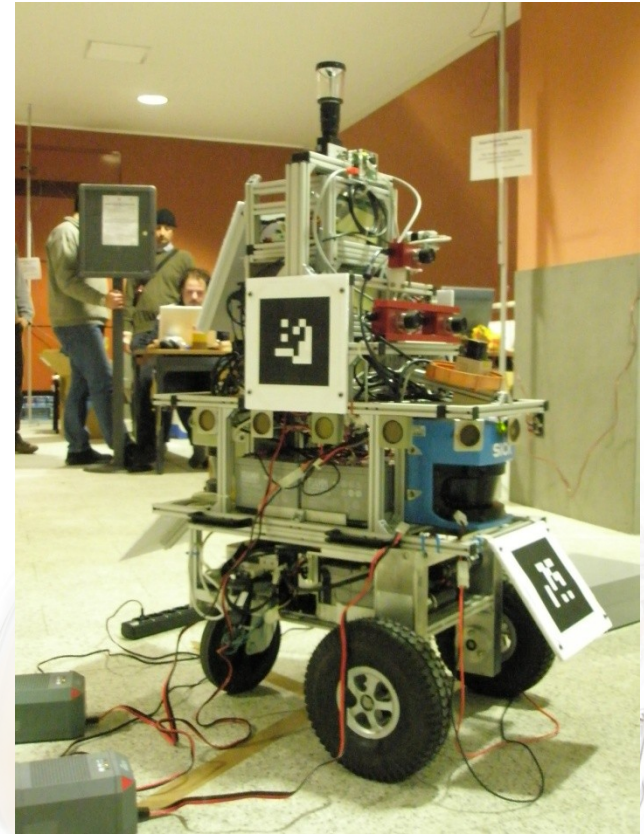
- Nowadays we feel the lack of tools and methods to compare and evaluate market strength products. To aim at this RAWSEEDS fosters publishing of:
 - Extended multi-sensor data sets for the testing of systems on real-world scenarios from different sensor perspectives
 - Benchmarks and methodologies for quantitative evaluation and comparison of algorithms (and eventually sensors)
 - Off-the-shelf algorithms, with demonstrated performances, to be used for research bootstrap and comparison.

www.rawseeds.org



RAWSEEDS Datasets

- Use of an extensive sensing suite
 - B/W + Color cameras (monocular)
 - Stereo cameras (SVS by Videre)
 - LRFs (SICK 2D & Hokuyo)
 - Omnidirectional camera (V-Stone)
 - Sonar belt
 - GPS and RTK-GPS (Outdoor GT)
 - Other proprioceptives (e.g., odometry, Inertial Measurement Unit)
- Sensors are synchronized and data acquired at the maximum frequency allowed by the three onboard PCs



Benchmarks Problems & Solutions

- Benchmark Problems (BPs) aim at testing algorithms:
 - Include detailed description of the task
 - Multi-sensor Data Set related to the task
 - Evaluation Methodology and Tools
- Benchmark Solutions (BSs) extend BPs with:
 - Description of the algorithm for solving the BP and possible implementation (src or binary)
 - Algorithm output on the BP dataset
 - Evaluation (using the BP methodology)



Data Collection & Validation



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Design of the Datasets

- Defined relevant scenarios beforehand
 - Indoor scenarios with offices, halls, corridors, flat and non-flat walls, doors & passages, windows, horizontal floors, ramps, stairs, elevators, and several pieces of furniture.
 - Outdoor scenarios where the robot moves in the open between buildings and the obstacles are comparable with those found along urban roads.
 - Mixed scenarios parts of the robot trajectory is surrounded by walls and/or roof and parts are located in the open.
- Different acquisition setups
 - Static and Dynamic environments (i.e., people walking around)
 - Different lighting conditions (i.e., natural daylight & artificial light)



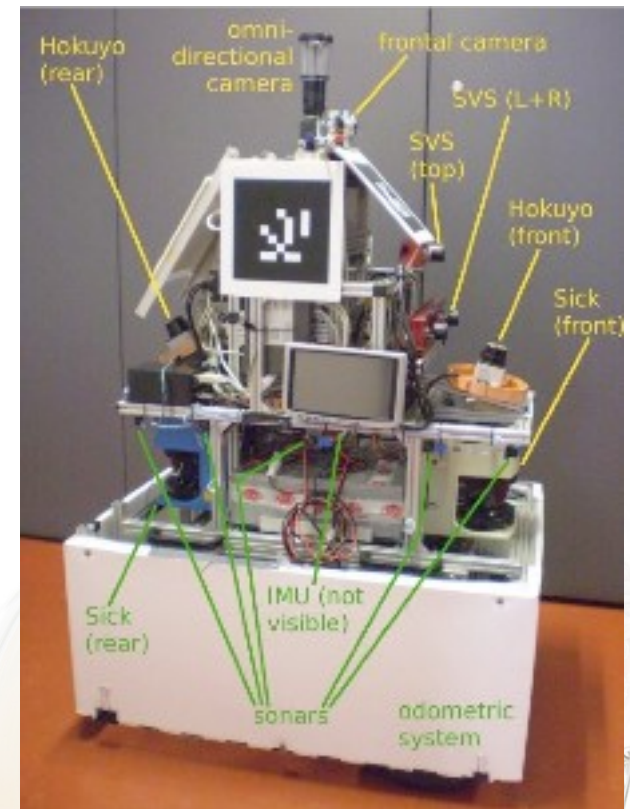
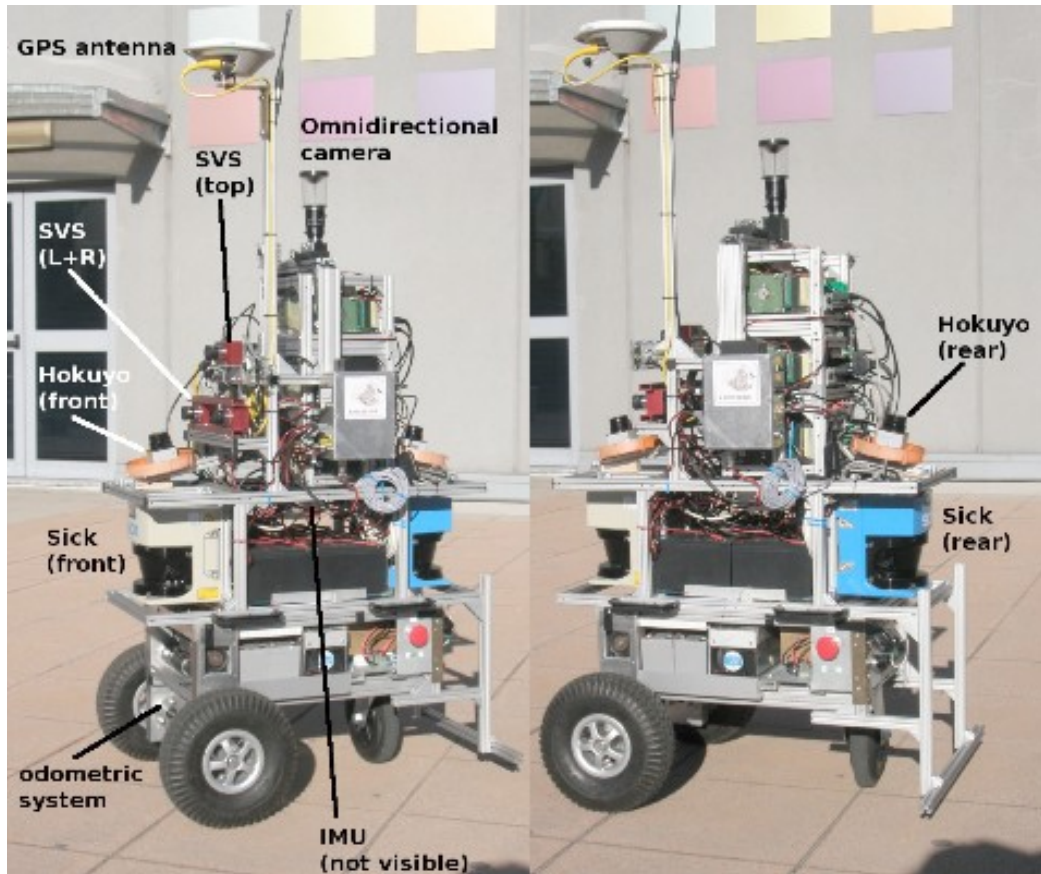
Indoor Locations in Bicocca



Outdoor and Mixed Locations in Bovisa



Sensors and sensor frame

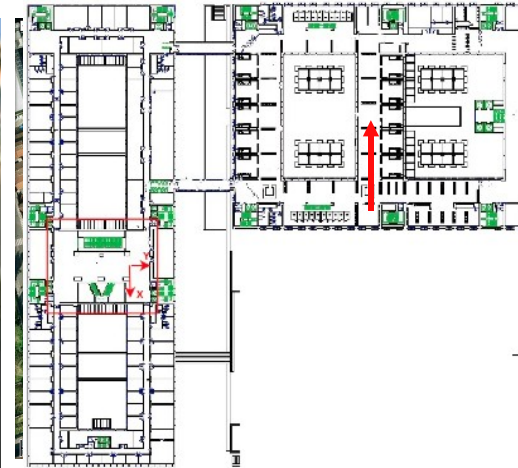


11 Datasets Collected

Many different scenarios:

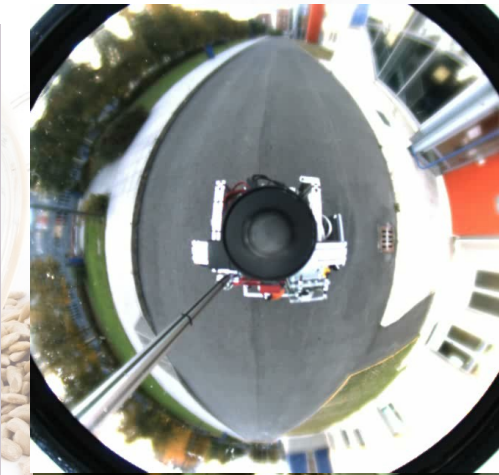
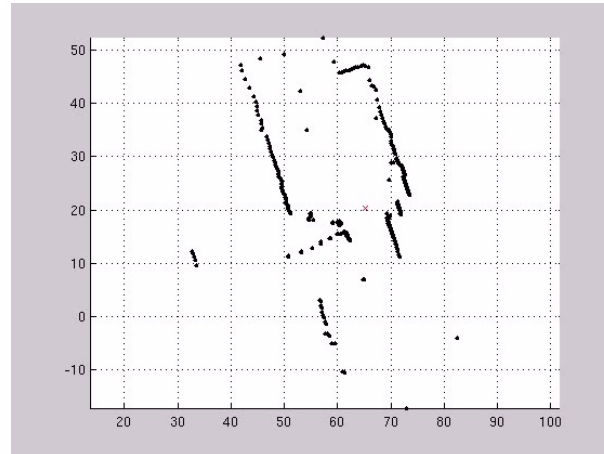
- Indoor

- 1 static lamps
- 1 static daylight
- 1 dynamic lamps
- 2 dynamic daylight



- Outdoor

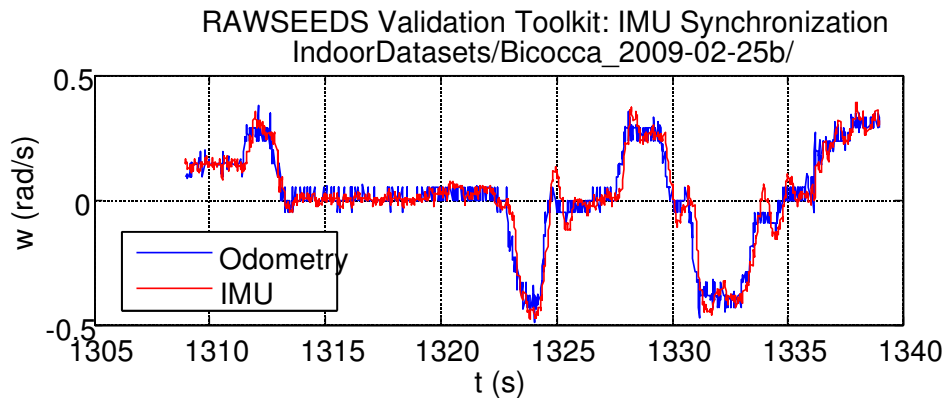
- 2 static
- 1 dynamic



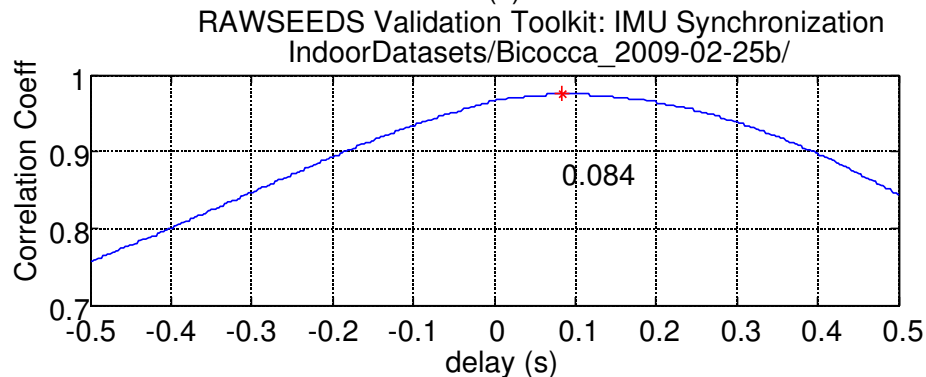
- Mixed

- 2 static
- 1 dynamic

Validation: IMU and Odometry

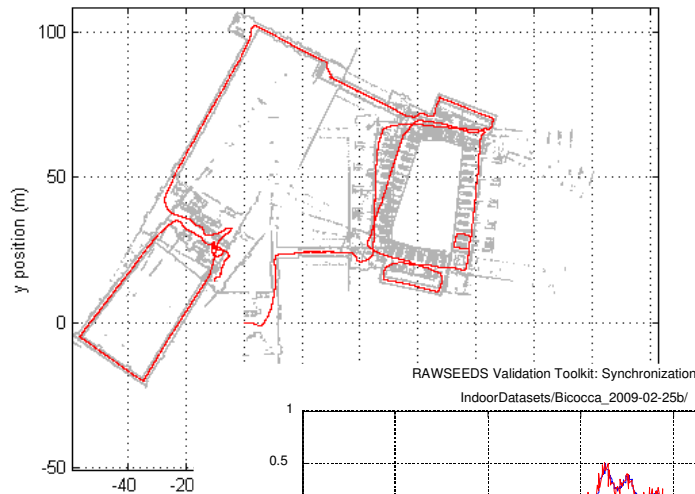


- IMU used as time base
- Delays found by correlation of angular velocities

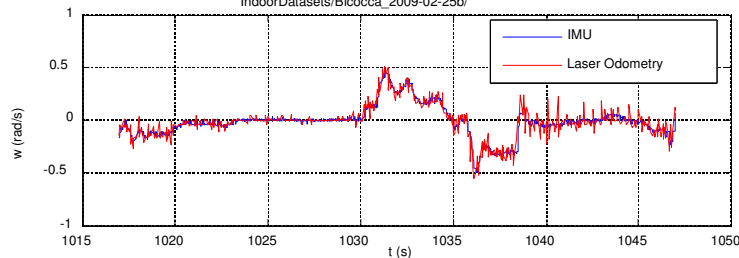


Validation: SICK Laser

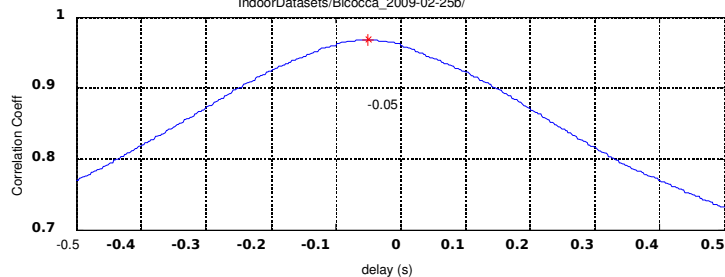
- Scan matching
- Correlation of angular velocities
- Map building with ALUFR Graph-SLAM



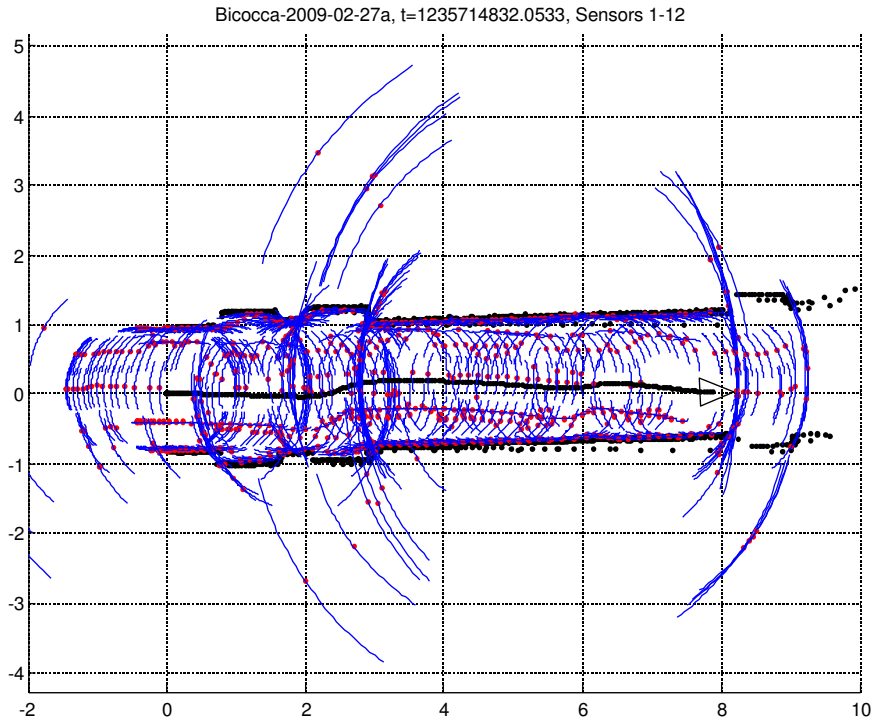
RAWSEEDS Validation Toolkit: Synchronization
IndoorDatasets/Bicocca_2009-02-25b/



RAWSEEDS Validation Toolkit: IMU-Laser Synchronization
IndoorDatasets/Bicocca_2009-02-25b/



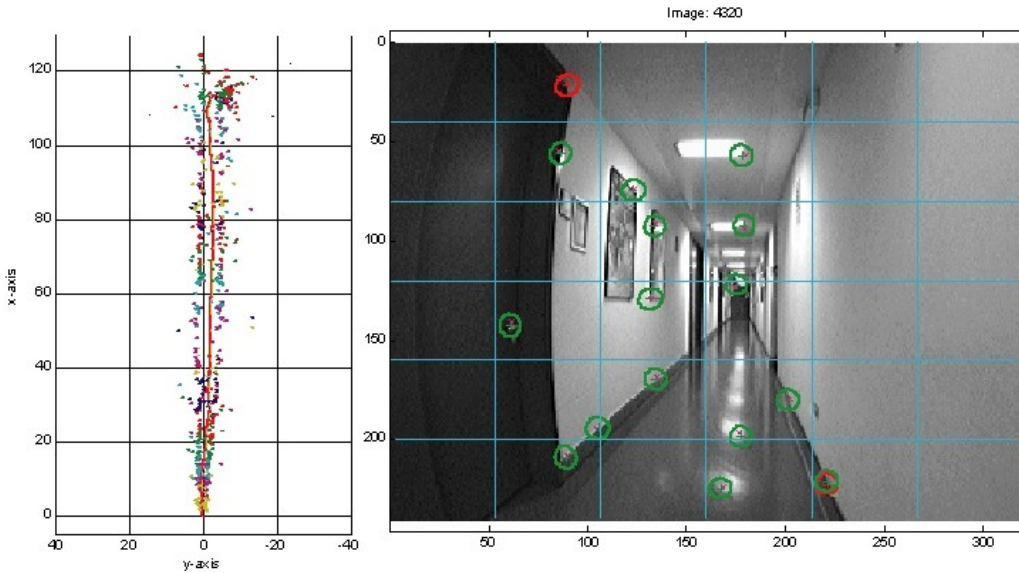
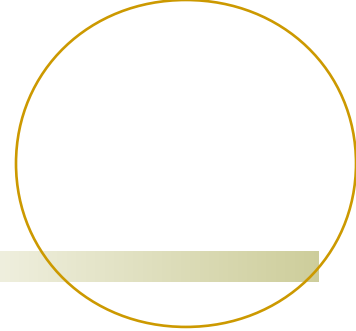
Validation: Sonar Belt



- Plot sonar returns + visual inspection
- Some spurious returns
 - typical in sonar data

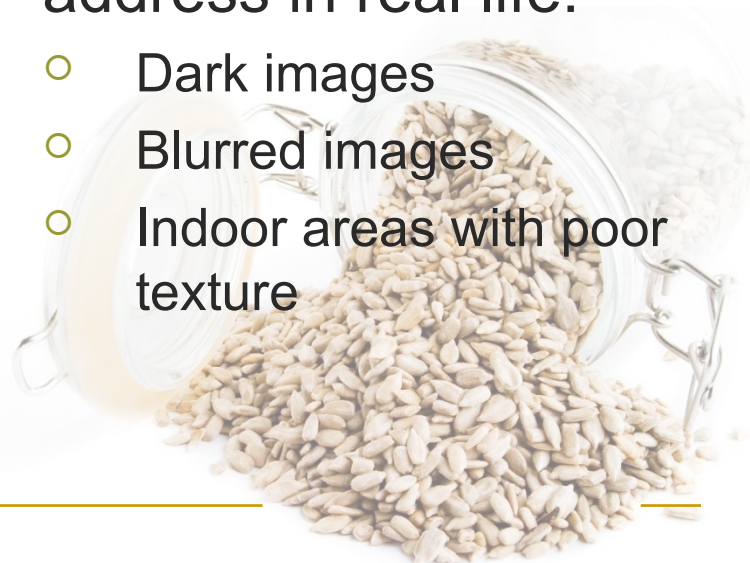


Validation: Monocular Vision



- Data density and quality verified running visual SLAM
- Typical issues that a SLAM algorithm must address in real life:

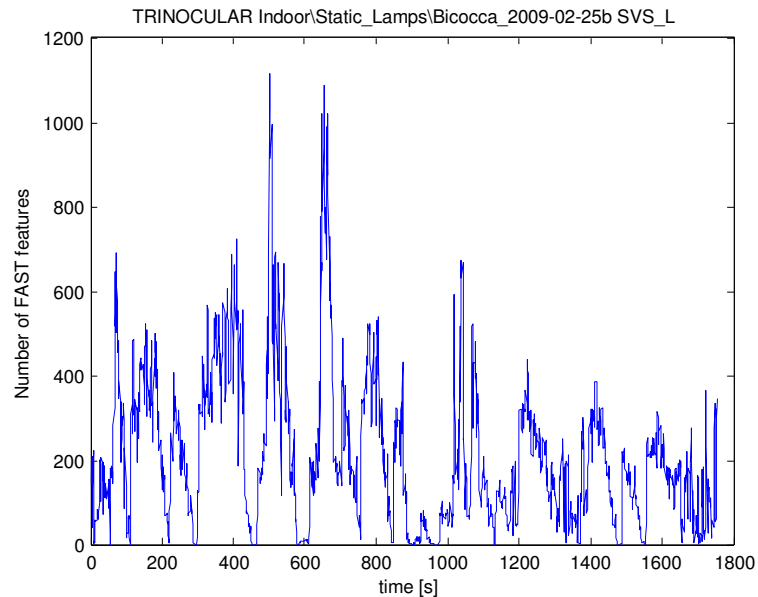
- Dark images
- Blurred images
- Indoor areas with poor texture



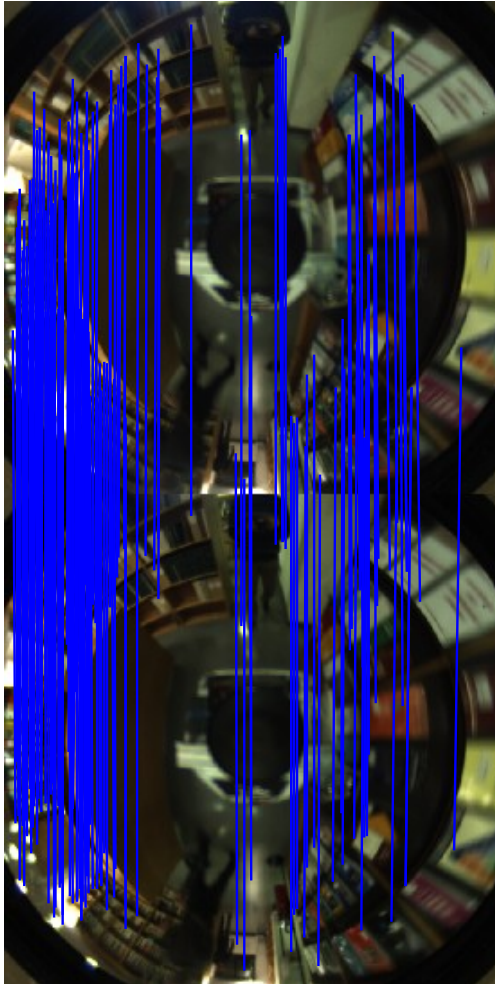
Validation: Trinocular Vision



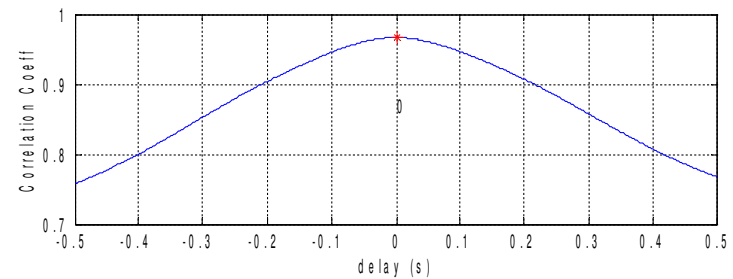
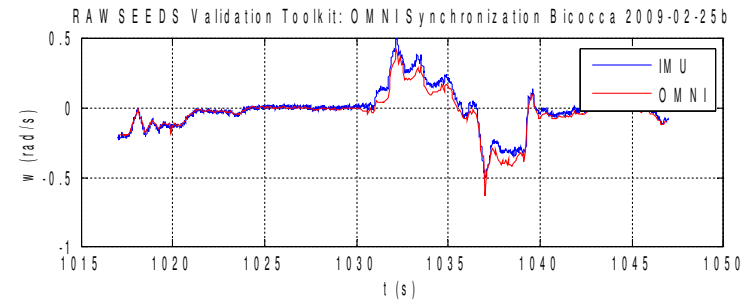
- Calibration and data quality verified by 3D reconstruction
- Feature density



Validation: Panoramic Vision



- FAST feature extraction and matching
- Synchronization



Ground Truth Collection



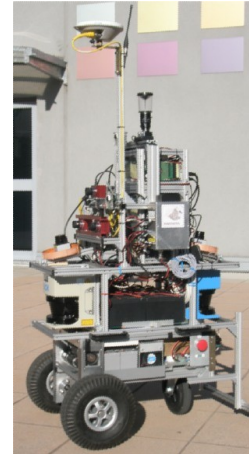
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Ground Truth Setup

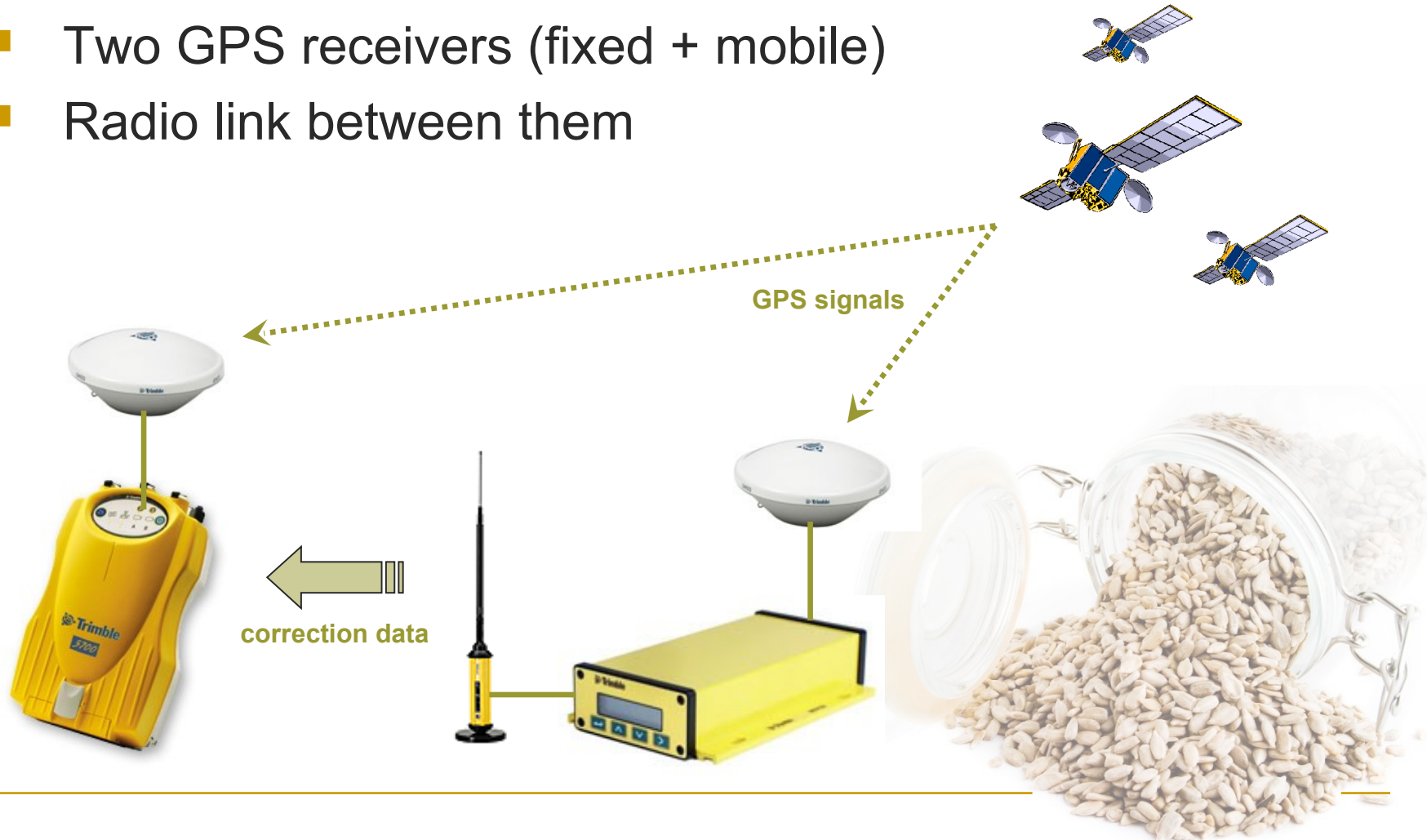
- GT Collection Systems

- Outdoor: RTK (Real Time Kinematic) GPS
- Indoor: vision-based (*GT-vision*) and LRF-based (*GT-laser*)



Outdoor GT: RTK GPS

- Two GPS receivers (fixed + mobile)
- Radio link between them



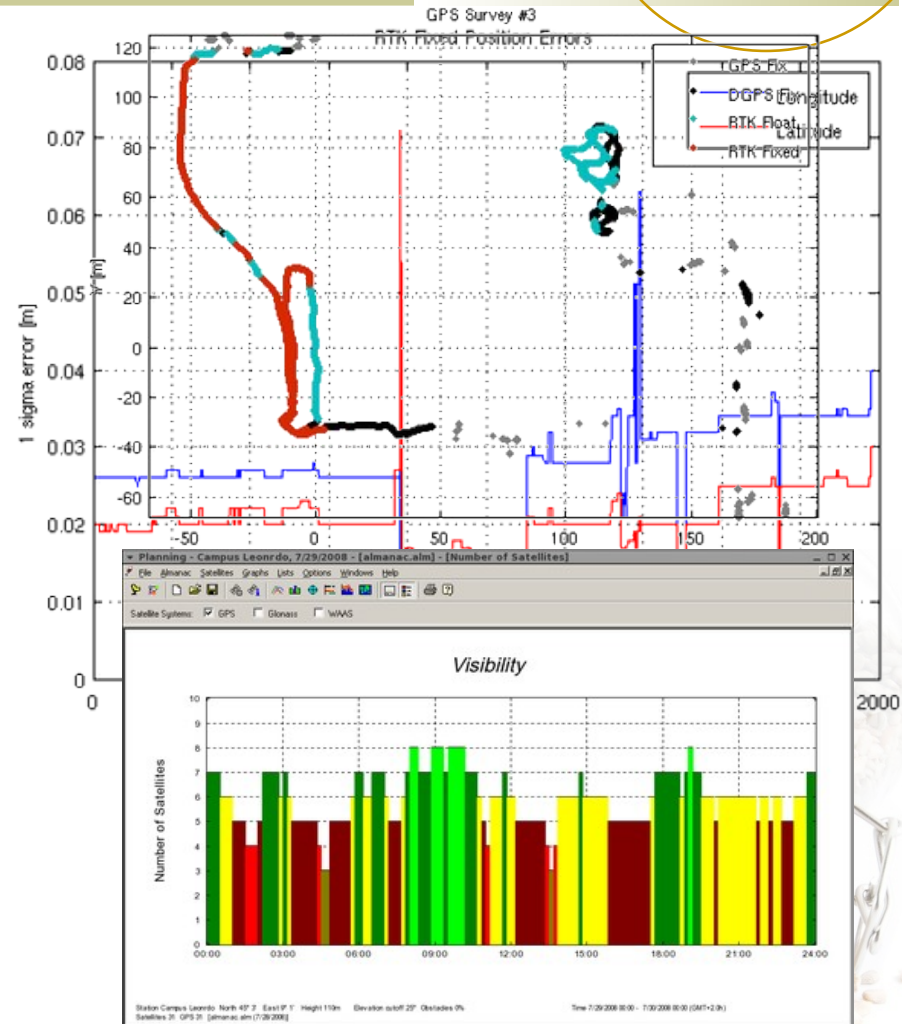
RTK GPS for Robotics

Advantages:

- absence of drift
- position data available over large areas
- easy setup... to a point
- high positioning precision

Drawbacks:

- does not operate indoors
- costly hardware
- extremely sensible to obstacles
- performance varies widely over time and space



Setup: Vision GT

5 cameras
(GigE Vision)



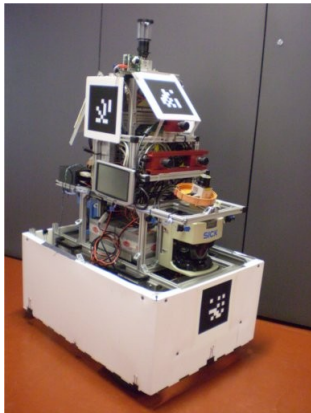
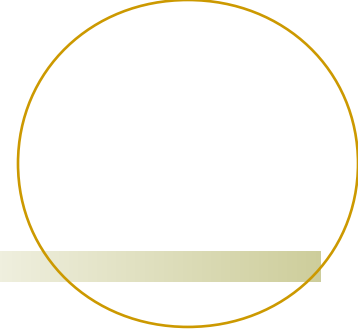
GigE switch



PC + sw



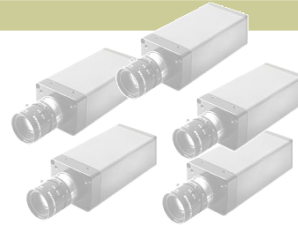
NIC



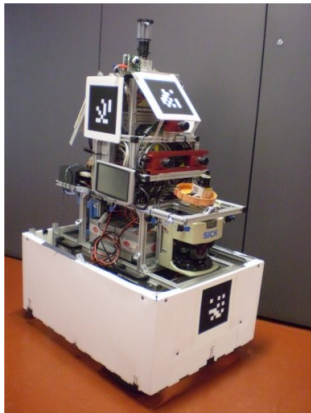
robot with visual tags



Setup: Laser GT



robot with outer hull



PC + sw



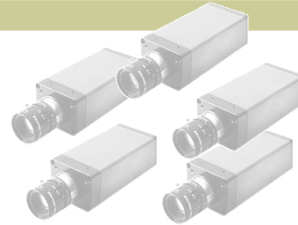
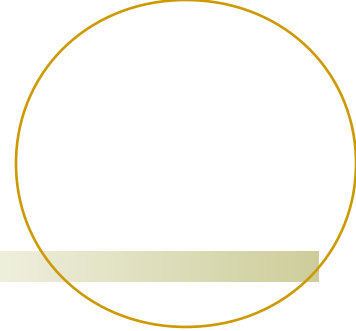
4 LRFs



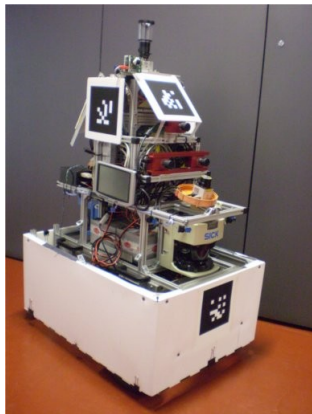
RS422 board



Setup: GT Synchronization



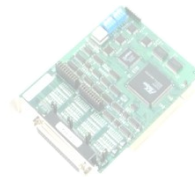
PC + sw +
PTP slave



robot with
wireless router
+
PTP master

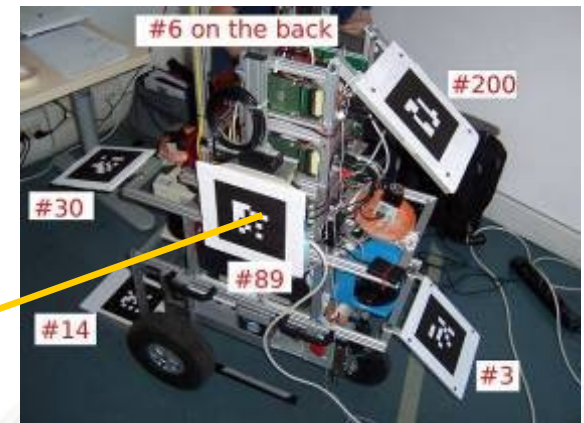
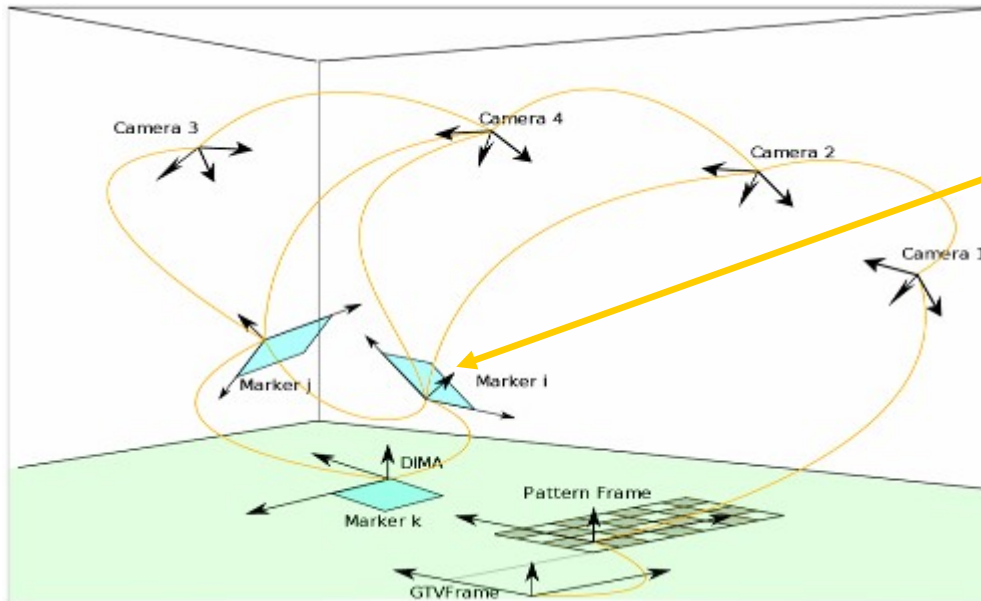


wireless NIC



Vision GT System

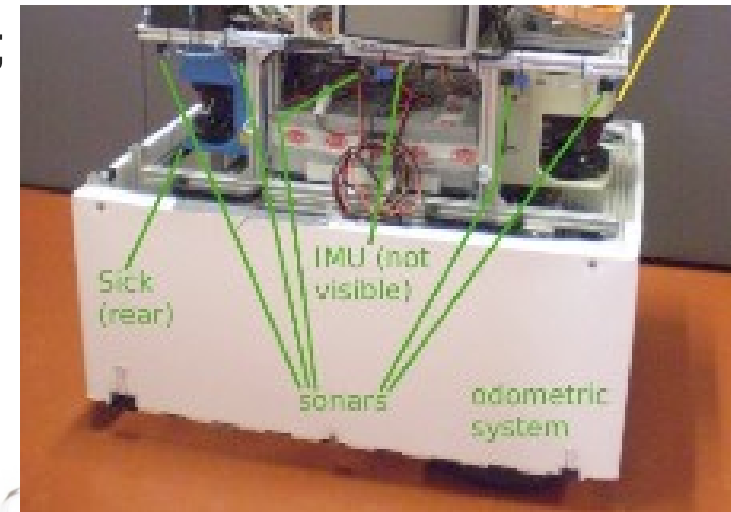
- Use a camera network to localize the robot
 - Good: Independent sensor
 - Bad: Requires (painful) setup/calibration
 - Doubt: Might not be accurate enough



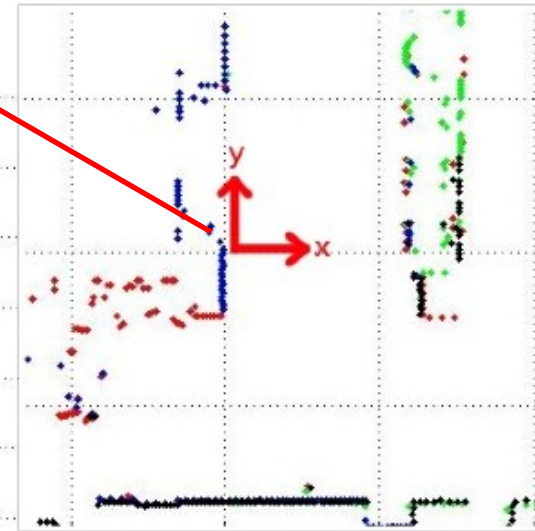
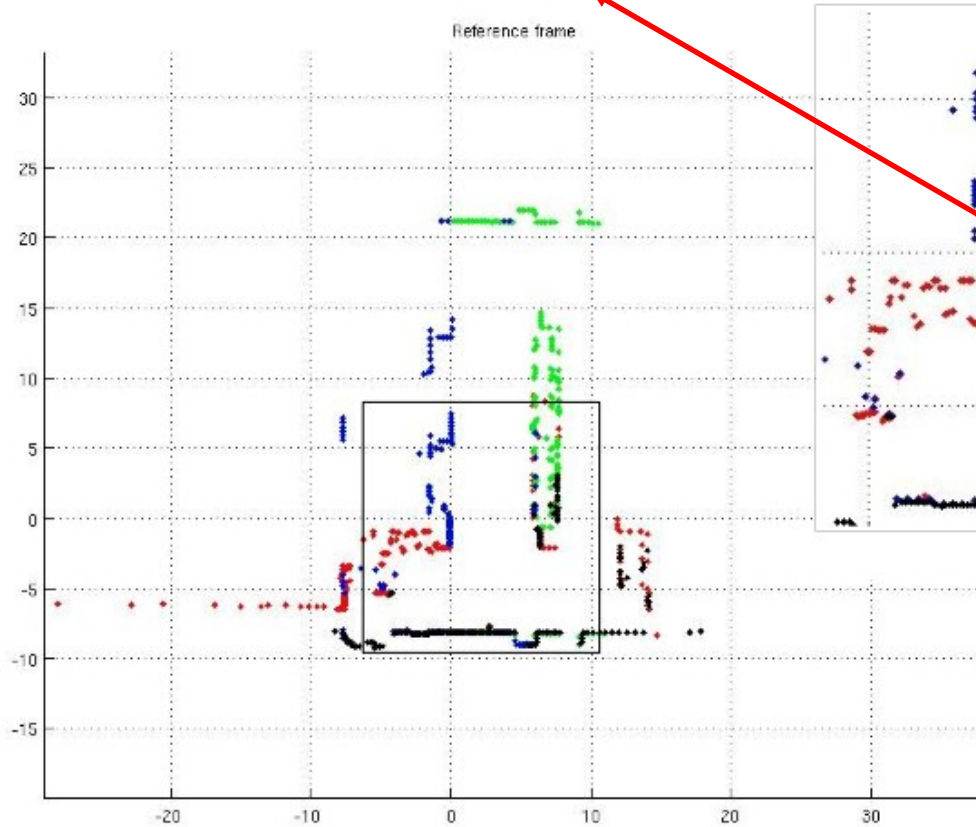
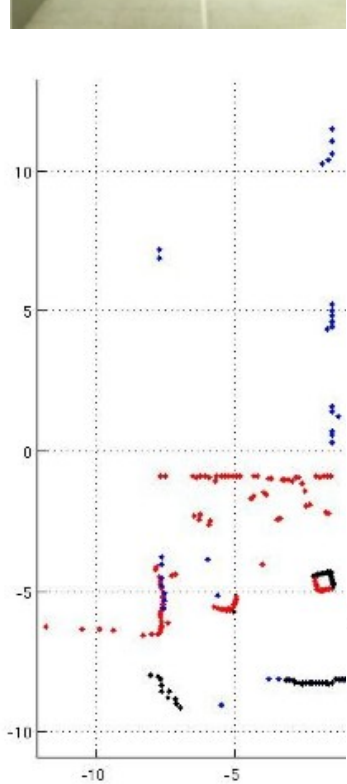
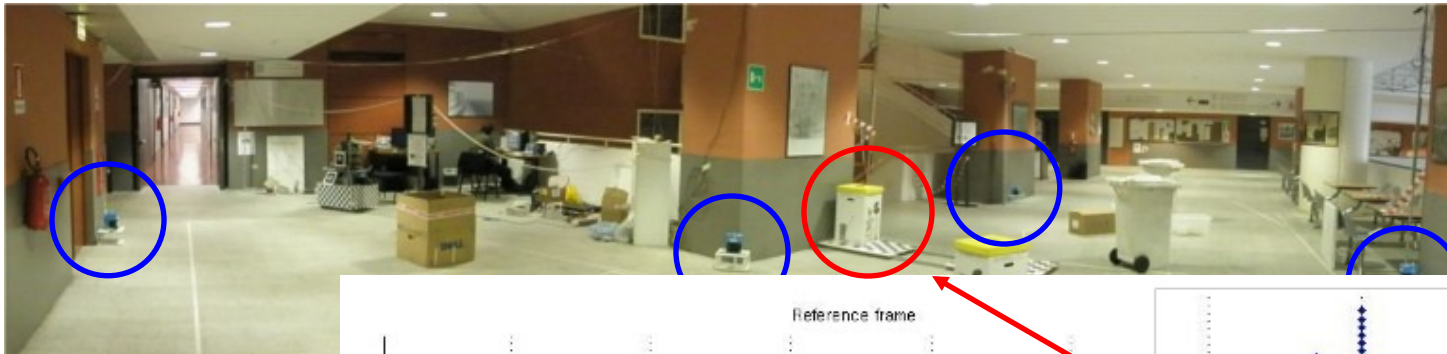
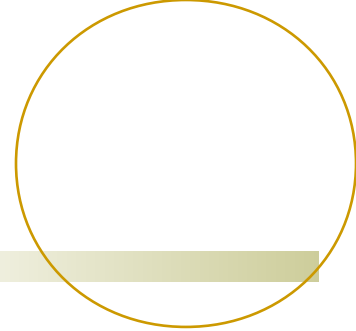
Required ~ 0.1 m accuracy

Laser GT System

- We developed another (offboard) poseGT system;
 - based on 4 sick laser-scanners;
 - area covered approximately as for Vision GT;
 - calibration (scan alignment) with ICP;
 - the robot model is a rectangle in the scans (the gown);
 - robot localization with ICP in the overall scan;

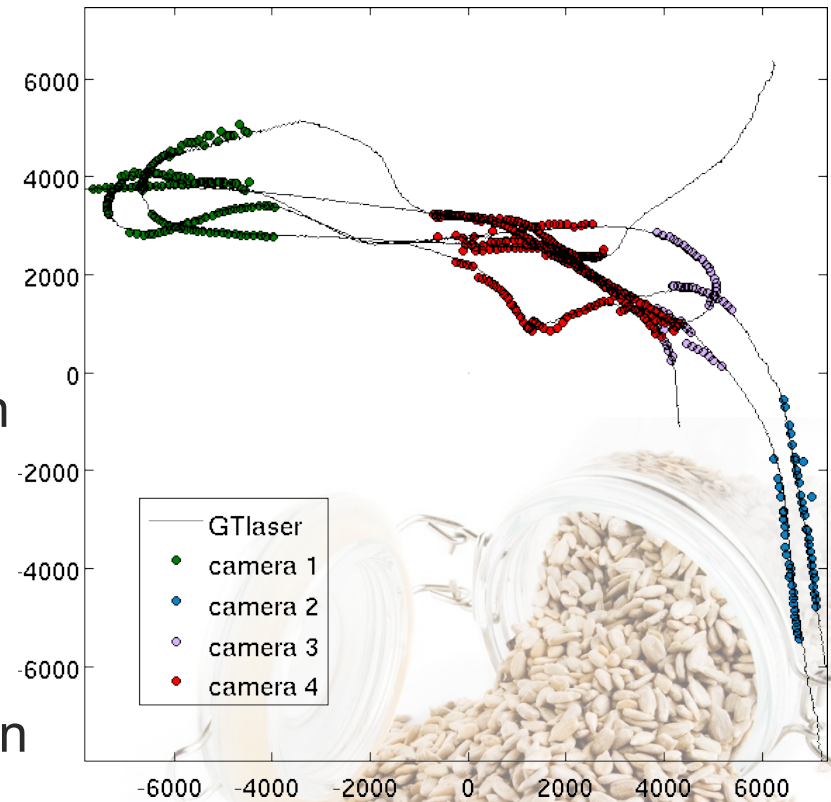


GT Systems Alignment



GT Accuracy

- Vision GT
 - $112 \pm 90\text{mm}$ in position
 - -0.8 ± 2.16 degs in orientation
- Laser GT
 - $20 \pm 11\text{mm}$ in position
 - 0.15 ± 1.56 degs in orientation
- Overall Accuracy
 - $19 \pm 11\text{mm}$ in position
 - -0.12 ± 1.56 degs in orientation



Benchmark Problems and Solutions



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Benchmark Problems (BPs)

- BPs are the union of:
 - the description of a task;
 - a dataset, as the input for the execution of the task;
 - a set of rating methodologies (metrics), for the evaluation of the results of the task execution.
- RAWSEEDS Metrics
 - ME (Mapping Error)
 - ATE (Absolute Trajectory Error)
 - REC (Rough Estimate of Complexity)
 - SLE (Self-Localization Error)
 - RPE (Relative Pose Error)

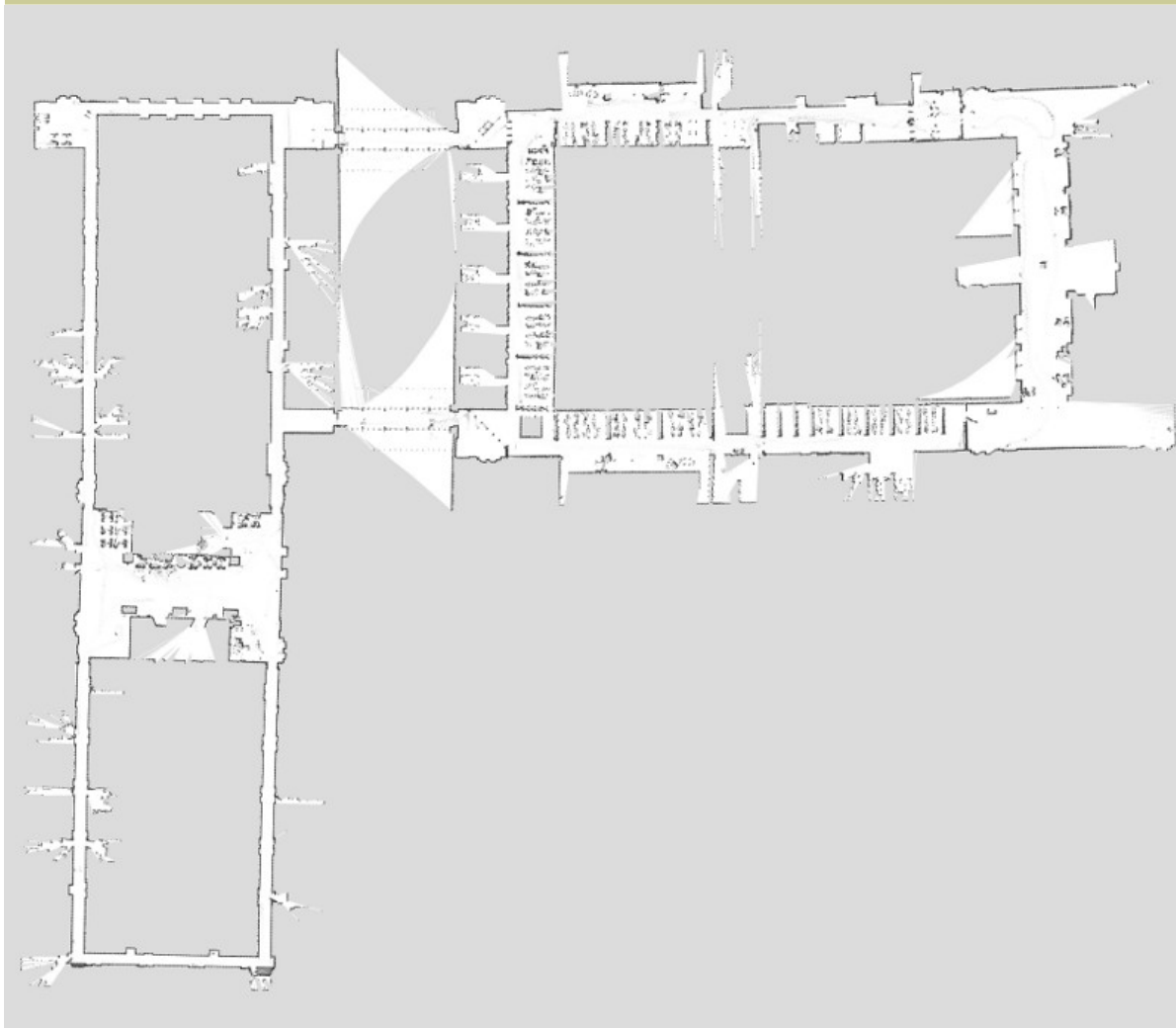
| | PROBLEM | SENSOR DATA |
|-----------------------------|--|---|
| Laser SLAM | perform a map building activity with SLAM (online) | laser, IMU and odometry from a dataset |
| Monocular SLAM | perform a map building activity with SLAM (online) | single camera, IMU and odometry from a dataset |
| Stereo SLAM | perform a map building activity with SLAM (online) | stereo camera, IMU and odometry from a dataset |
| Trinocular SLAM | perform a map building activity with SLAM (online) | trinocular IMU and odometry from a dataset |
| Omnidirectional vision SLAM | perform a map building activity with SLAM (online) | omnidirectional vision, IMU and odometry from a dataset |
| Sonar SLAM | perform a map building activity with SLAM (online) | sonar sensors, IMU and odometry from a dataset |
| Multisensor SLAM | perform a map building activity with SLAM (online) | streams from more than one sensor, for a dataset |

Benchmark Solutions (BSs)

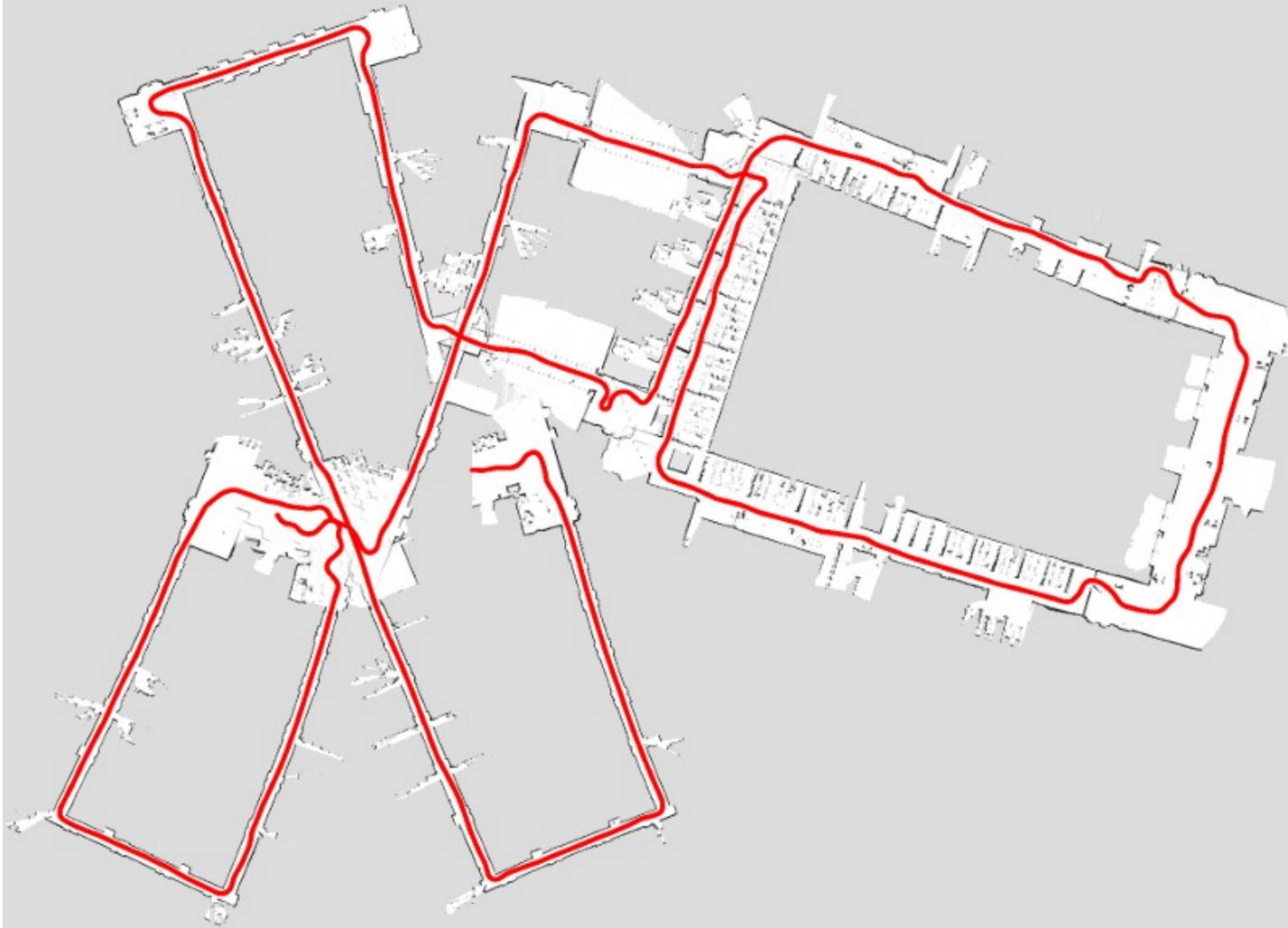
- Generation of ready to use solutions for the RAWSEEDS BPs, using the following algorithms
 - Laser Based
 - Scan-matching [ALUFR]
 - Rao-Blackwellized Particle Filters [ALUFR]
 - Graph-based SLAM [ALUFR]
 - Vision Based
 - Monocular and Stereo SLAM[UNIZAR]
 - Trinocular SLAM [UNIMIB + POLIMI]
- User supplied solutions are foreseen through RAWSEEDS website



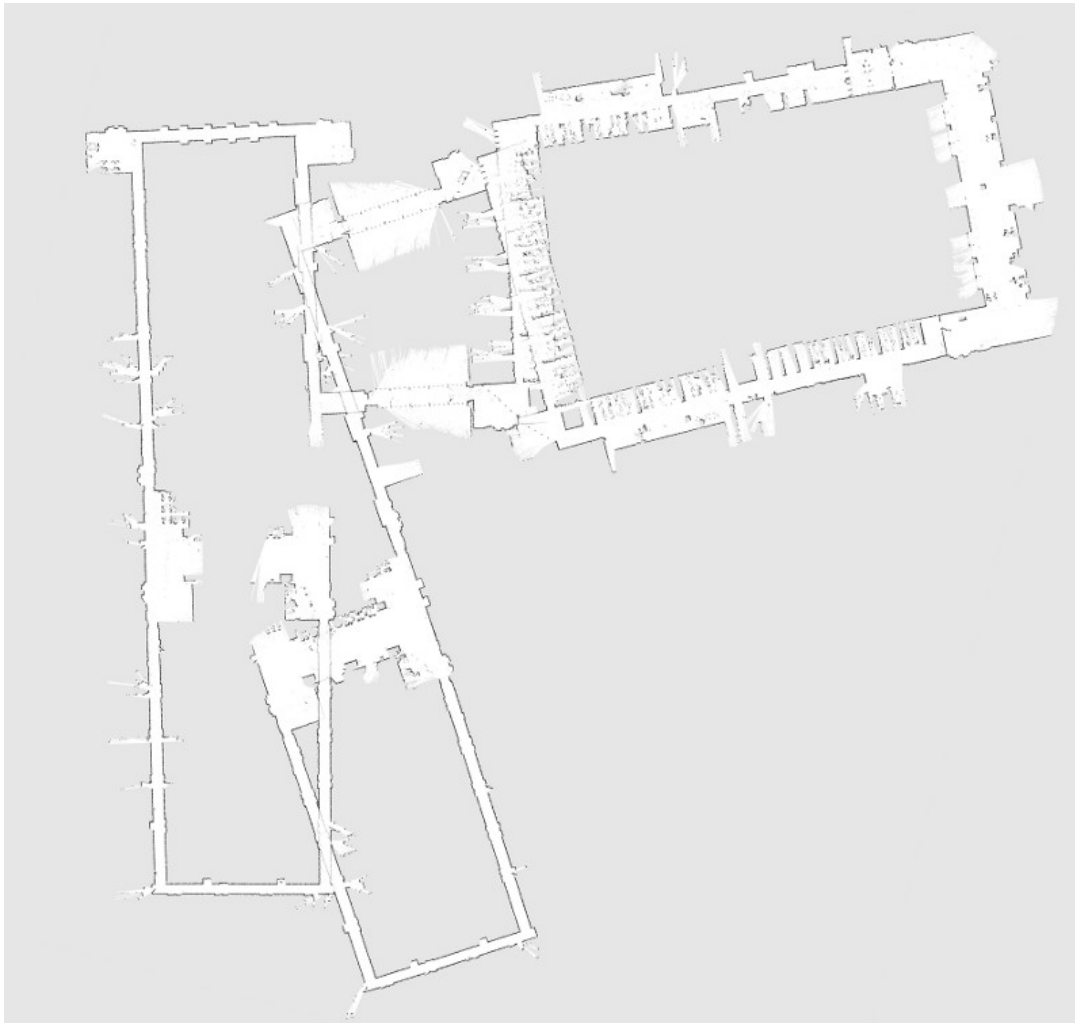
Laser-based SLAM Indoor (target)



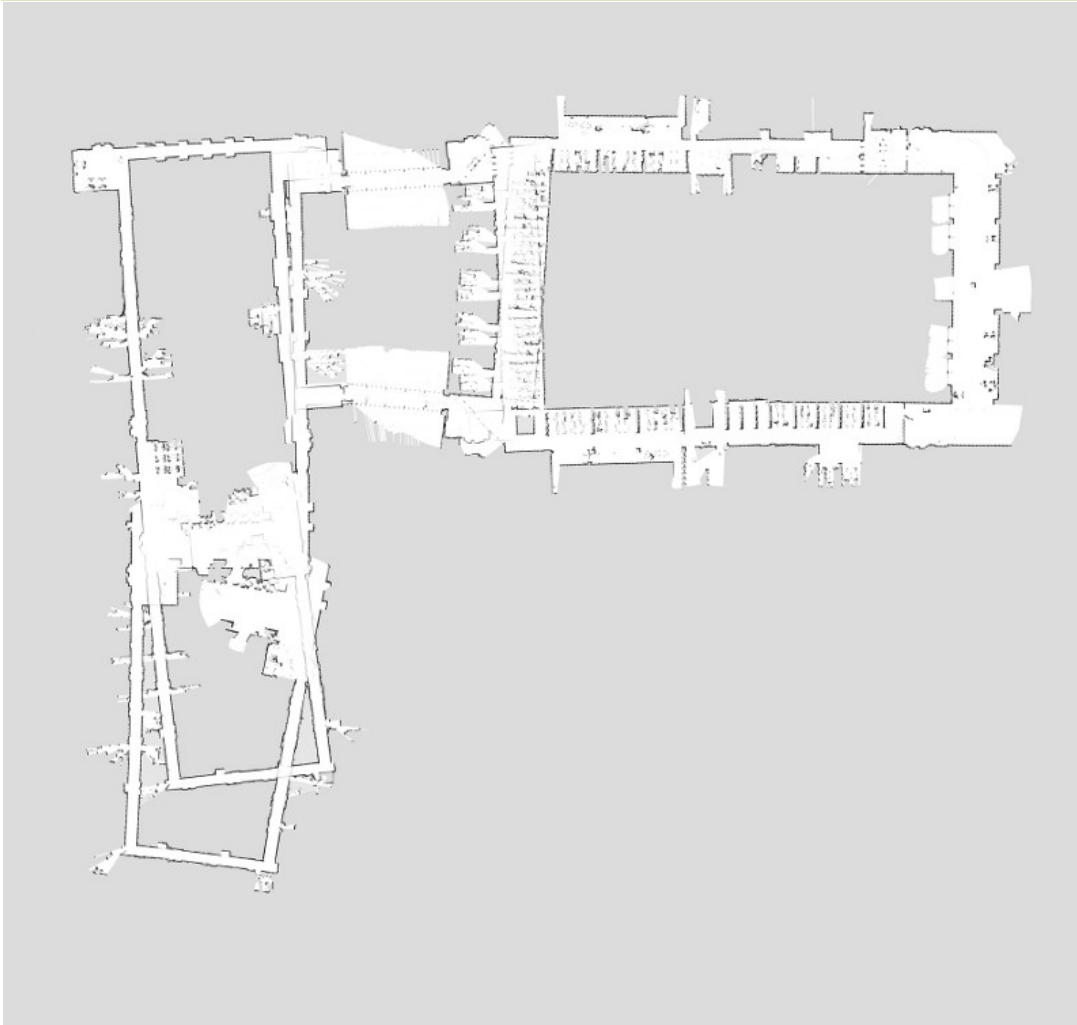
Laser-based SLAM Indoor (input)



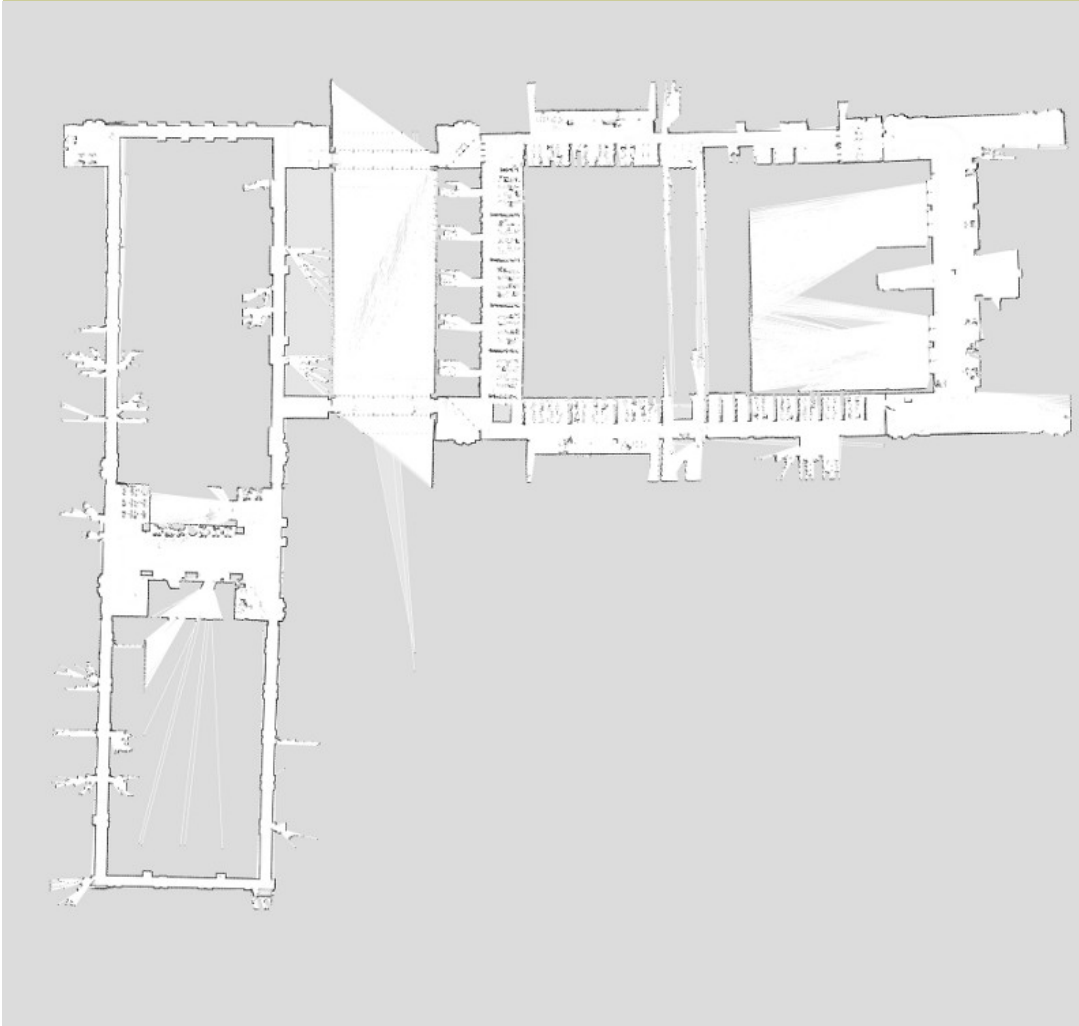
Laser-based SLAM Indoor (vasco)



Laser-based SLAM Indoor (rb-pf)



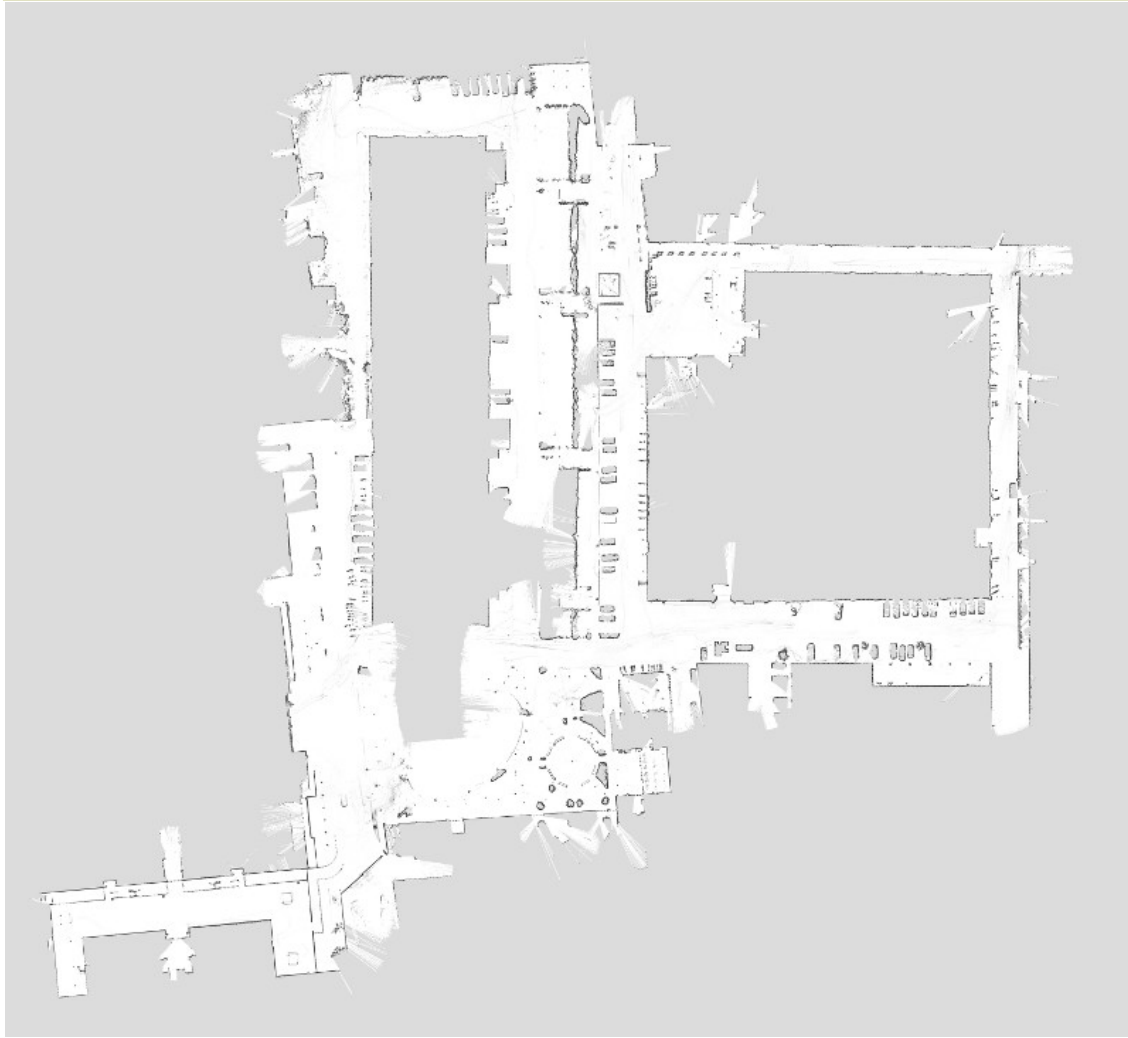
Laser-based SLAM Indoor (graph)



graph-mapper



Laser-based SLAM Outdoor (target)



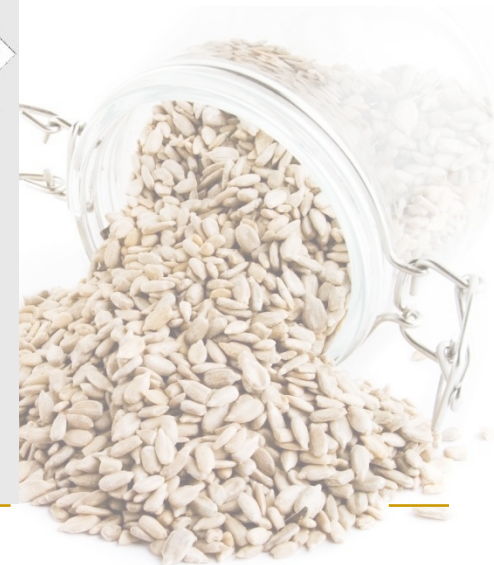
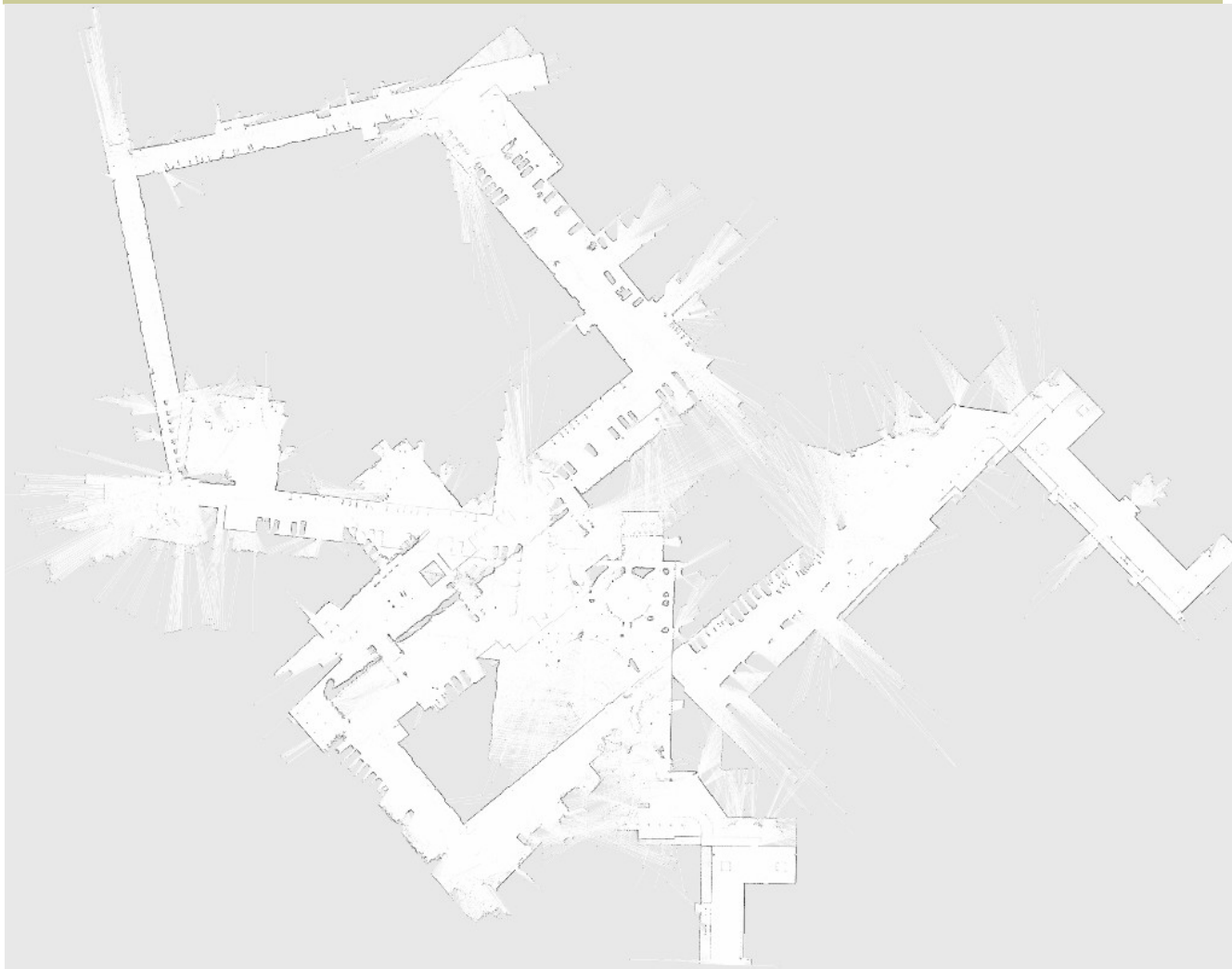
Laser-based SLAM Indoor (input)



Laser-based SLAM Indoor (scan)



Laser-based SLAM Indoor (rb pf)



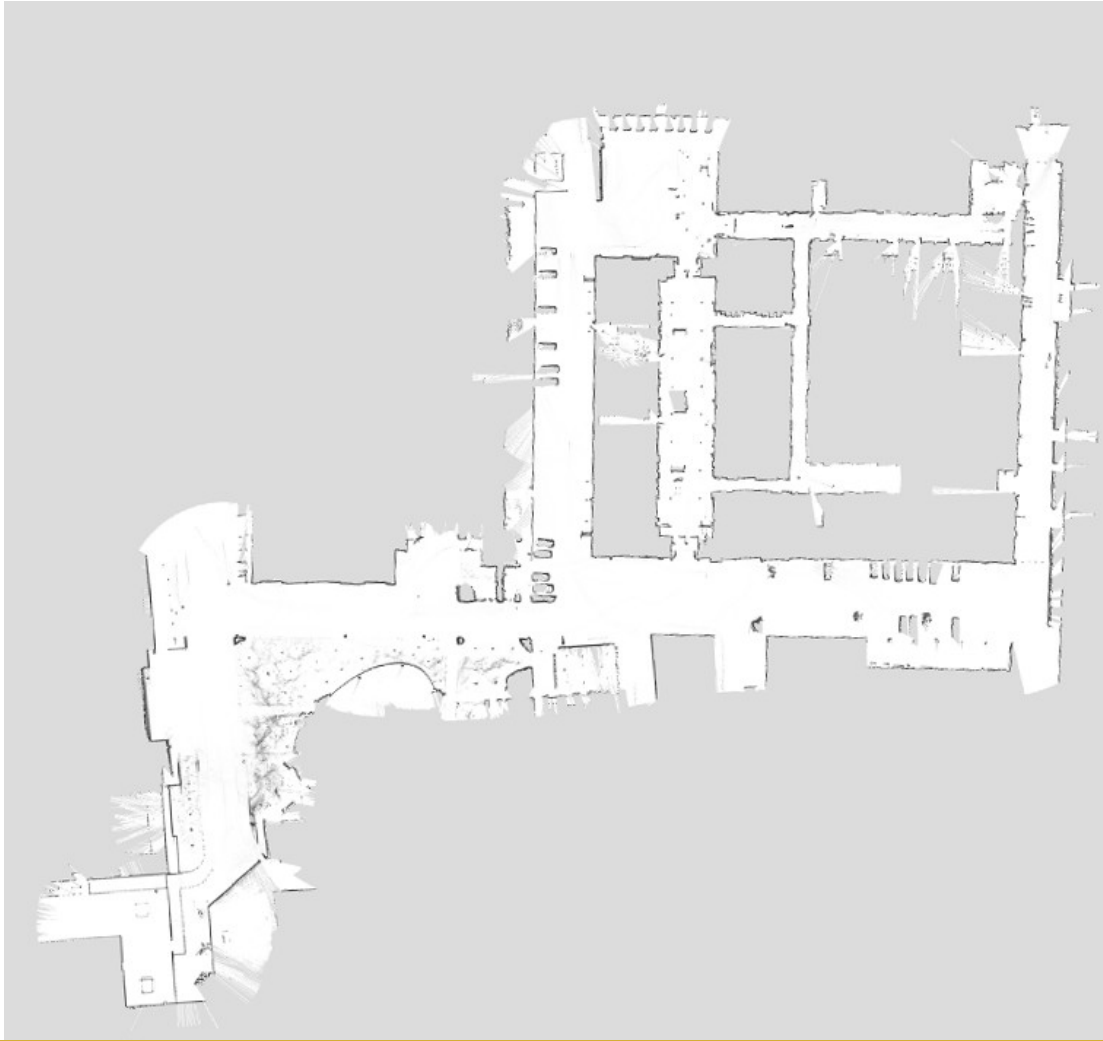
Laser-based SLAM Indoor (graph)



graph-slam



Laser-based SLAM Mixed (target)



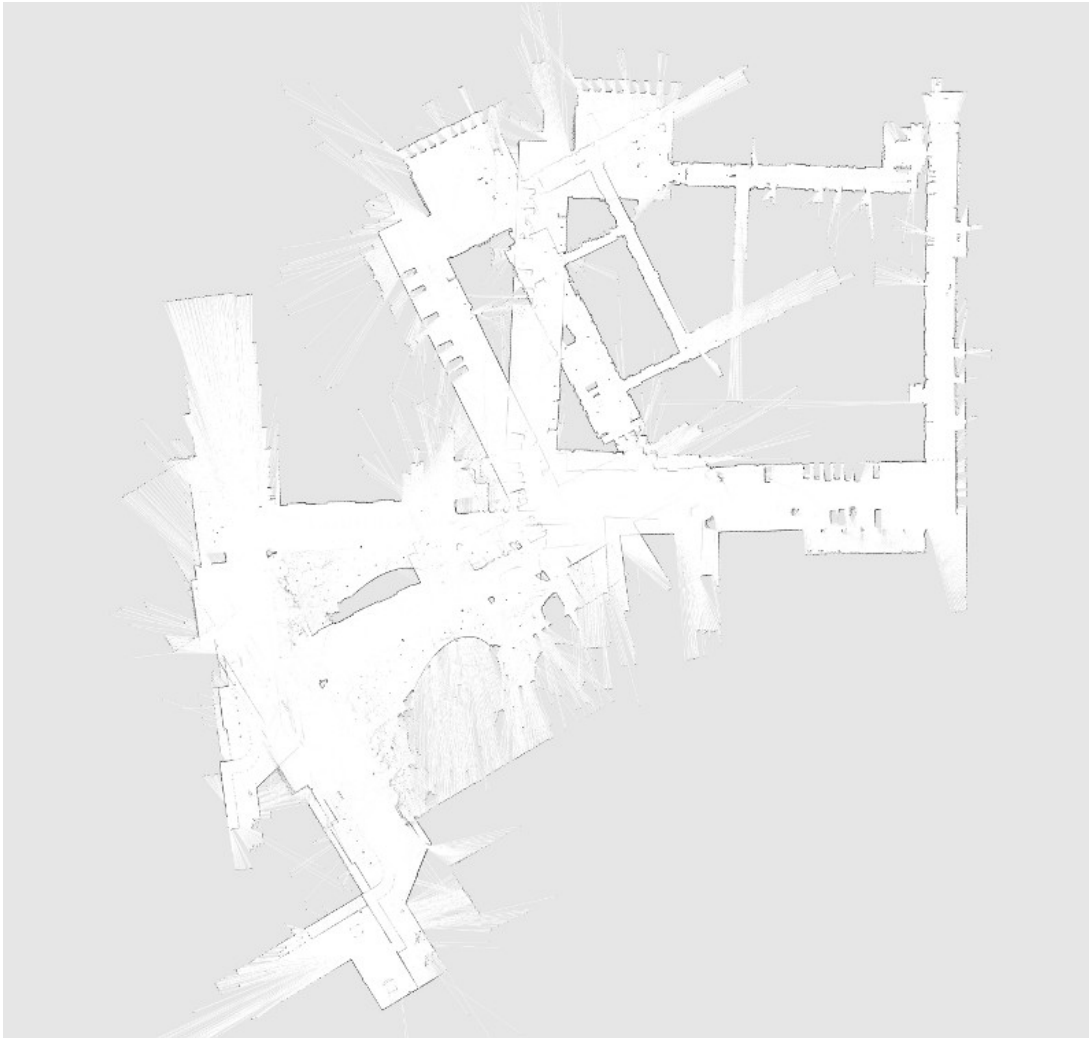
Laser-based SLAM Mixed (input)



Laser-based SLAM Mixed (scan)



Laser-based SLAM Mixed (rb-pf)



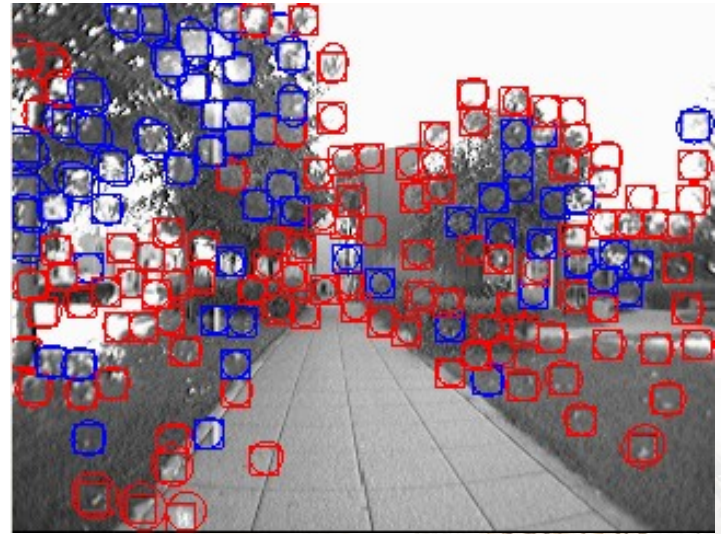
Laser-based SLAM Mixed (graph)



graph-slam



Monocular SLAM: Images used

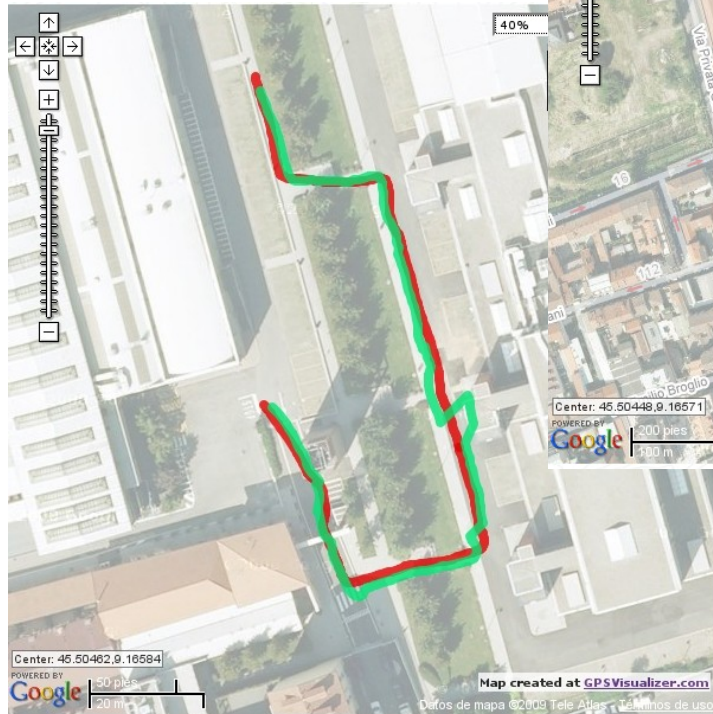


RAWSEEDS Outdoor
Datasets

High number of
image features per
frame (~100)

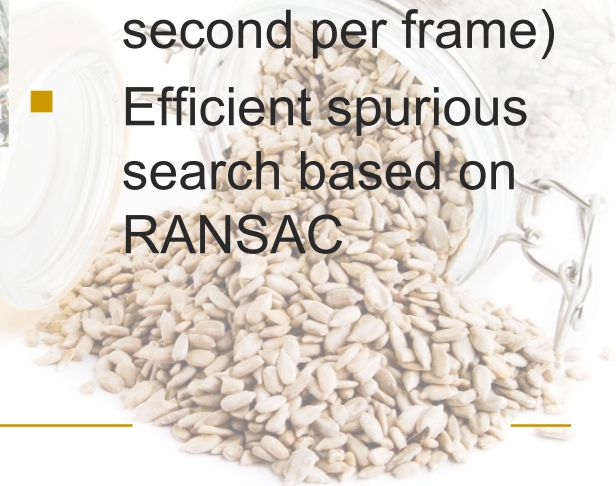
Monocular SLAM Results

153 metres
trajectory;
5400 images

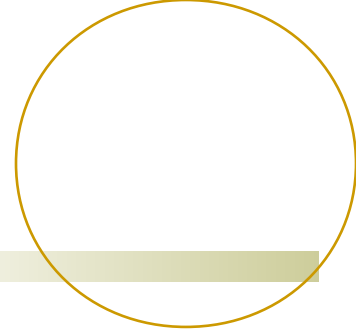
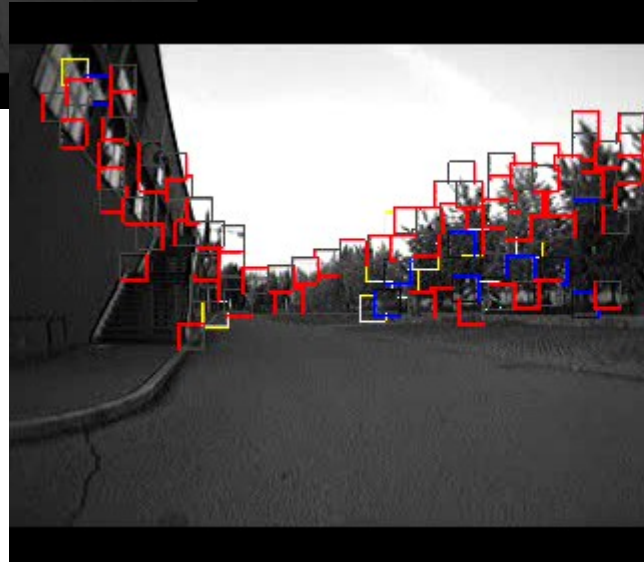
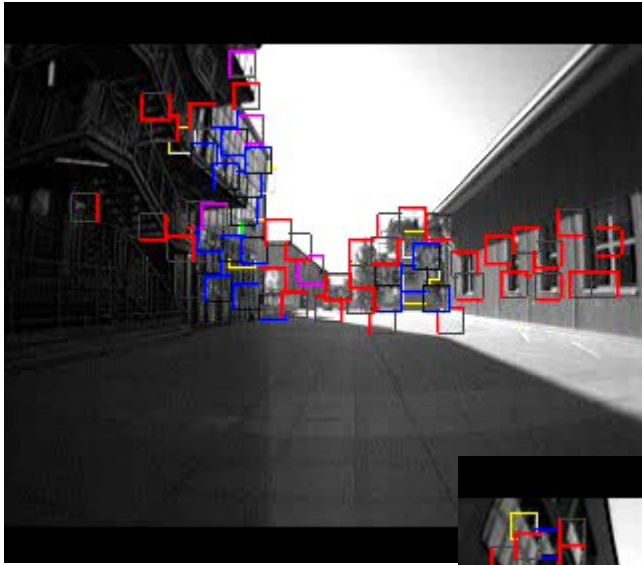


650 metres
trajectory;
24180 images

- Low error ($\sim 1\%$ of the trajectory)
- Longest trajectories ever using filtering-based visual estimation
- Near real-time processing (~ 1 second per frame)
- Efficient spurious search based on RANSAC



MonoSLAM: Results



Trinocular SLAM

- 3D segments extracted from trinocular images are directly used as features.
- Hierarchical approach with sub-maps
 - Local maps constructed by EKF and arranged in a global graph.
 - Global consistency achieved by graph-optimization.



Conclusions & Discussion

- The RAWSEEDS benchmarking toolkit soon available!

- Multisensorial datasets with ground truth
- Well defined benchmarks with metrics
- Off-the shell solutions to compare with

www.rawseeds.org

- What's after RAWSEEDS?

- More solutions ... are expected!
- More problems ... are welcome!
- More datasets ...
 - One platform is there, but collection has a costs!
 - What about other platforms (automotive, aerial, underwater)
- After perception we should benchmark decisions ...

