Marine Systems & Robotics

Unit 04 – AUV Localisation in challenging environments

http://impact.uni-bremen.de/

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Components 1

Keeping things watertight and floating

2

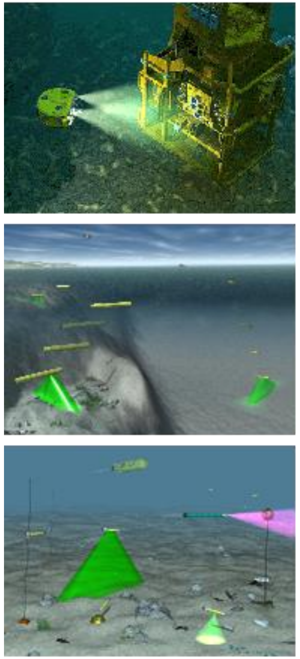
Why localisation?

Localisation is a key area for reliable navigation
Global positioning
Position with respect to the environment

Enabling factor for **Real World Application**

Why challenging environments?

Main Interest: Persistent Autonomy



- operate successfully while unsupervised
- operate for extended lengths of time
- operate in environments which are not completely known
- apart goals in response to unexpected events and disturbances
- recover from errors in task execution

Field Robotics

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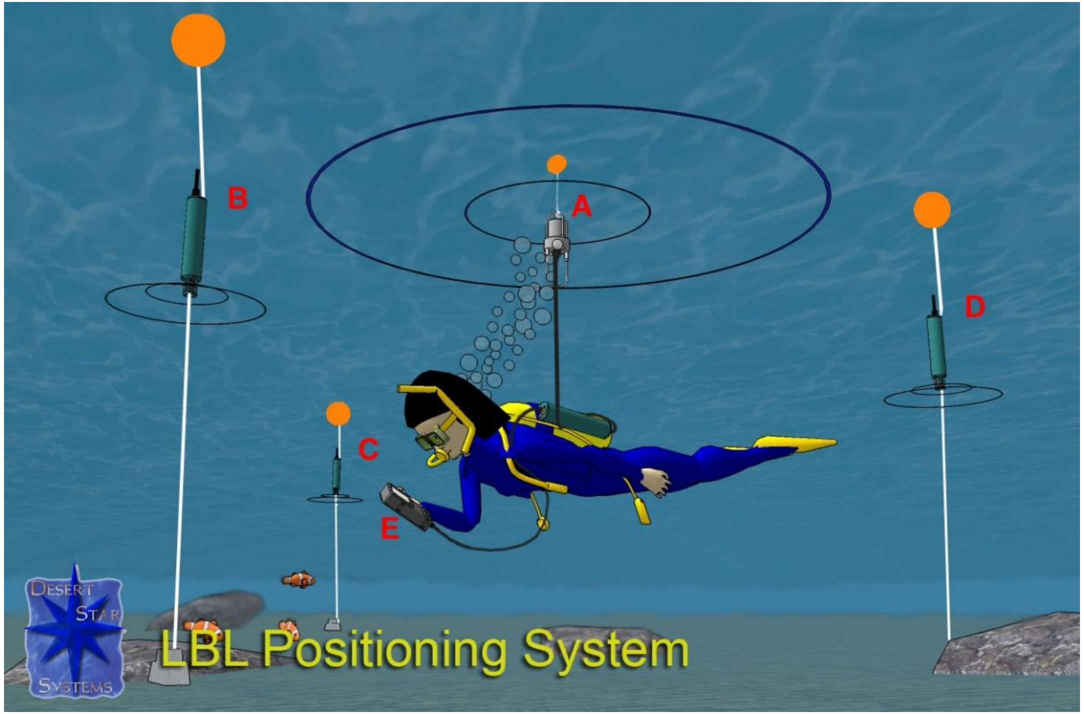
Marine Robotics

Localisation

Acoustic Localisation



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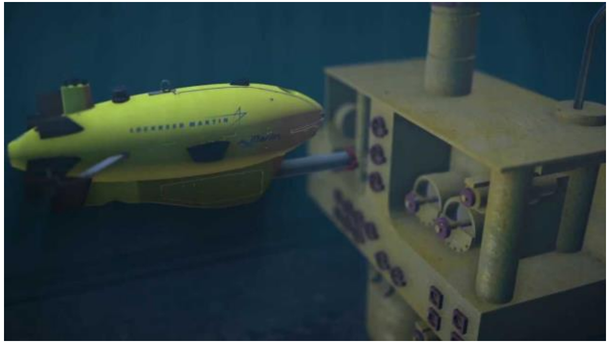
Localisation based on sensor data processing

Presence of structures
Noisy state estimation
Sensors (generally sonar underwater, laser scanner for surface)

Particle Filters



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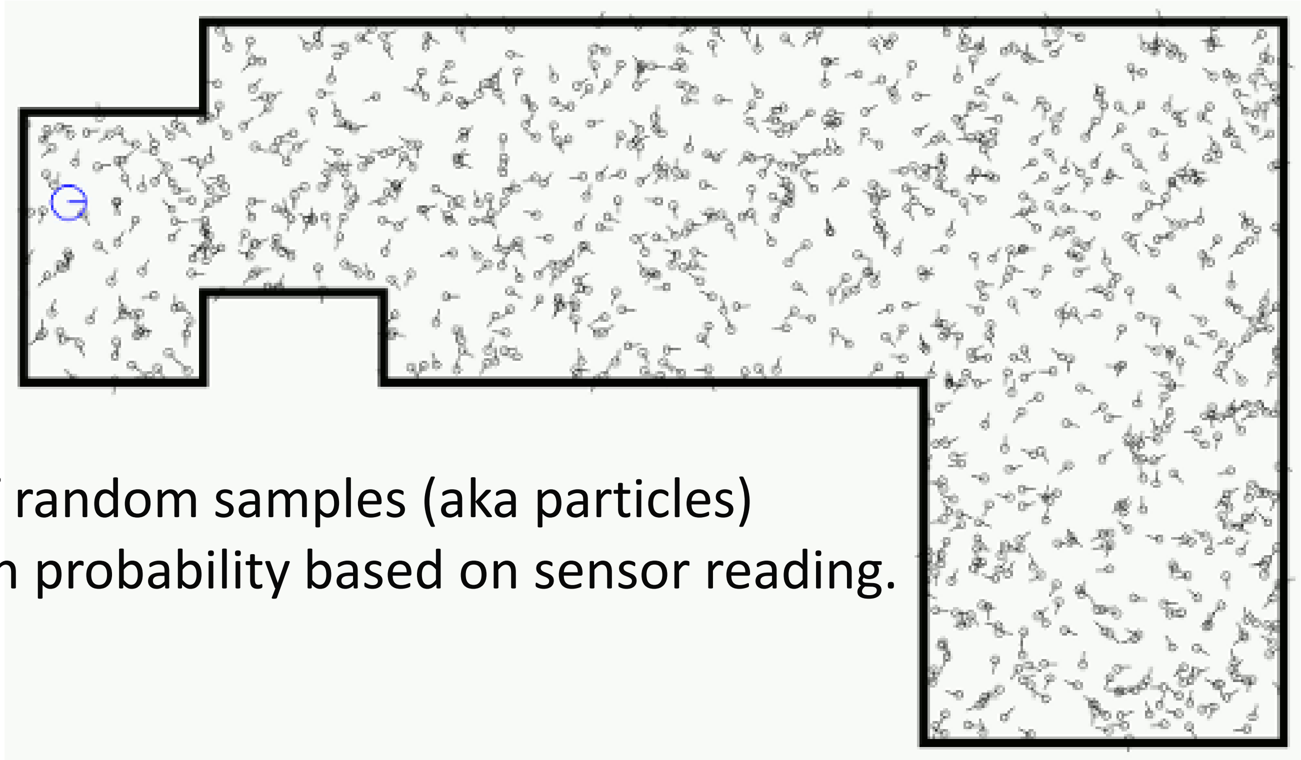
Monte Carlo Localisation

Repeated Random Sampling

- Idea: Represent belief by random samples
- Estimation of non-Gaussian, nonlinear processes

Monte Carlo filter, Survival of the fittest,
Condensation, Bootstrap filter, Particle filter

Monte Carlo Localisation



Start with lots of random samples (aka particles)
Weight each with probability based on sensor reading.

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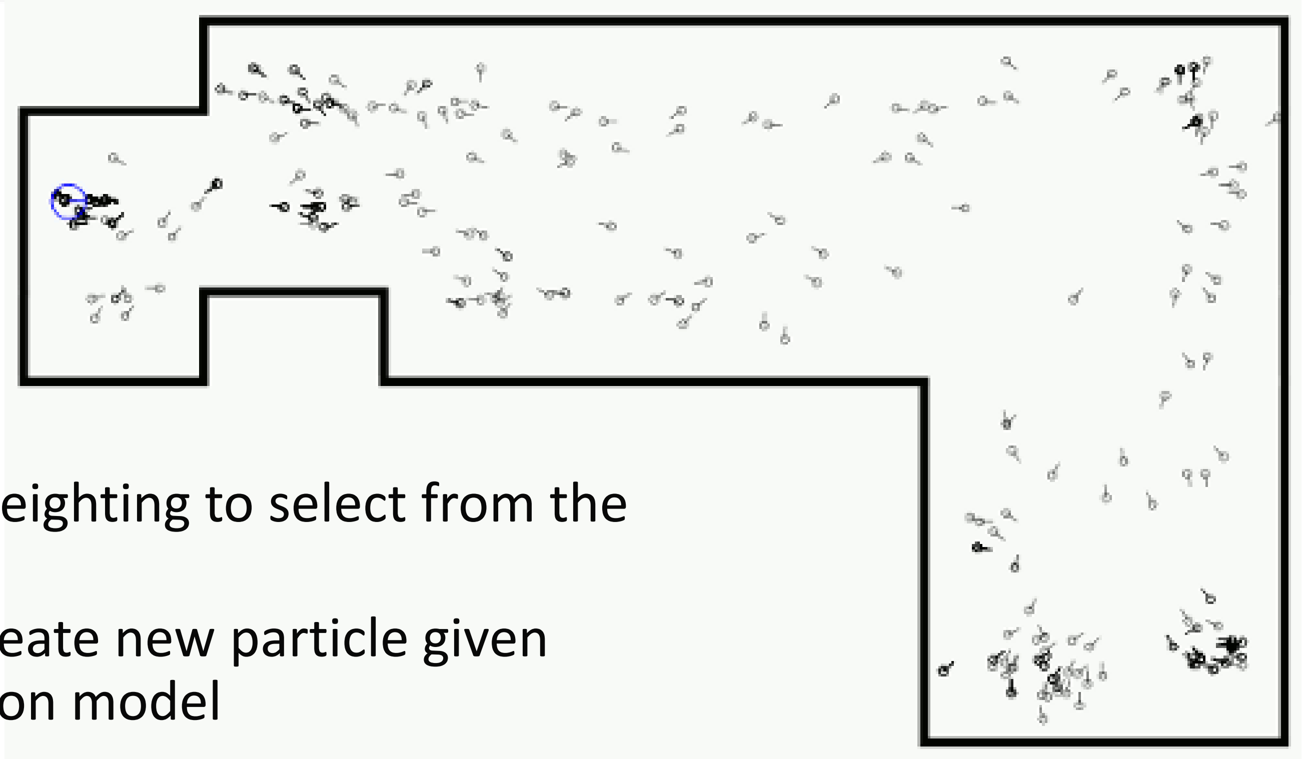
Monte Carlo Localisation

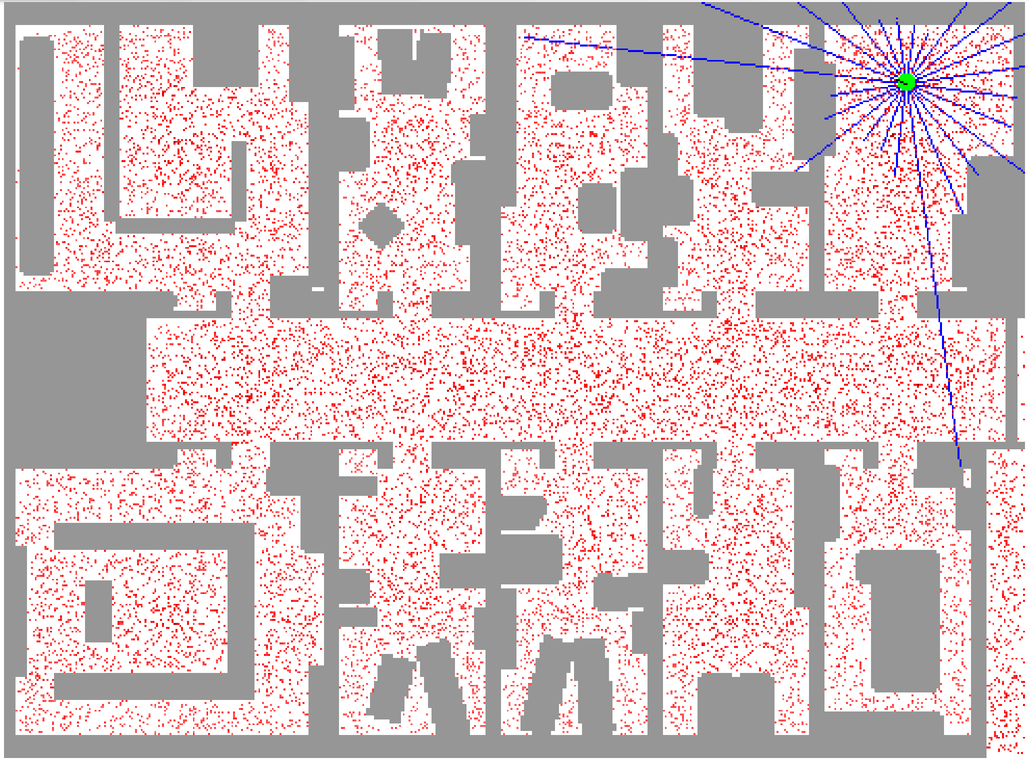


Given an action a,

Use importance weighting to select from the old particles

Probabilistically create new particle given action and motion model

Monte Carlo Localisation

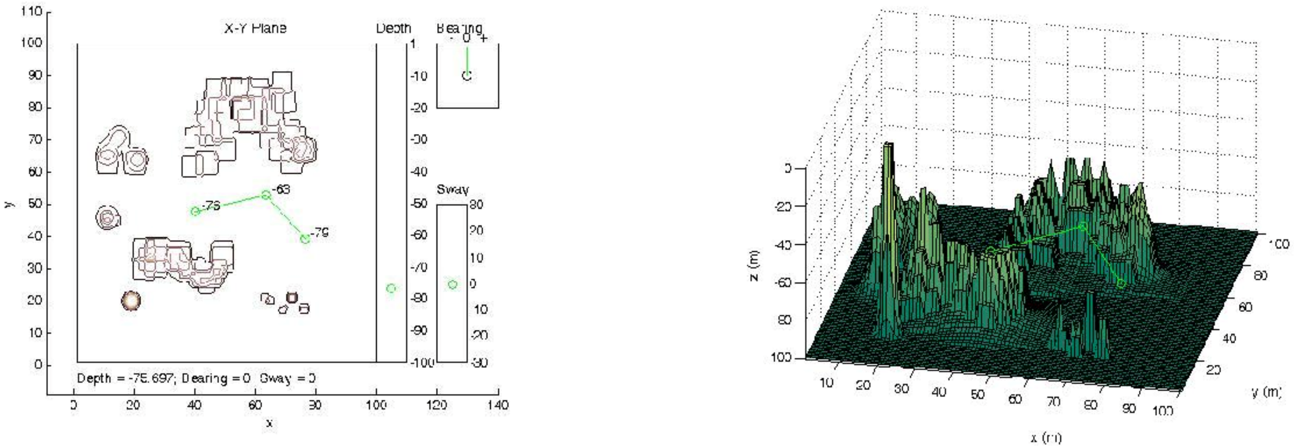


First Approaches

Geometric

Data processing

Algorithmic improvements



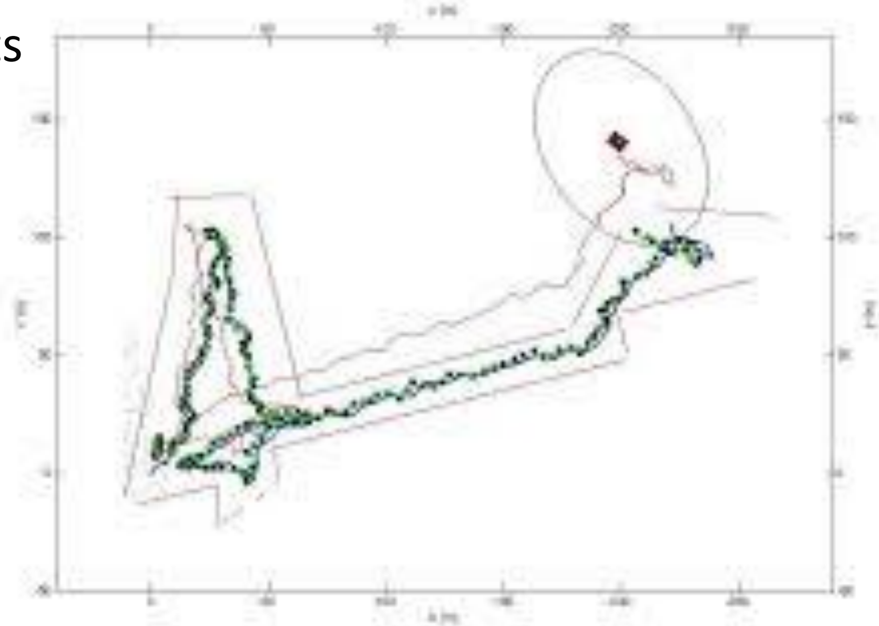
(a) settings for the trajectory (b) 3D map

First Approaches

Geometric

Data processing

Algorithmic improvements



Open Challenges?

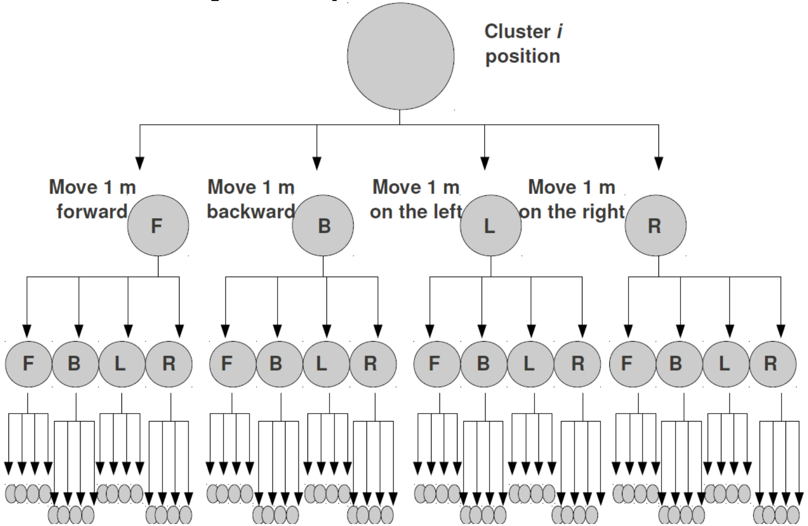
Data processing is passive!
→ uncertainty reduction is not sought
Motion planning needs to be addressed!

When do we need this?

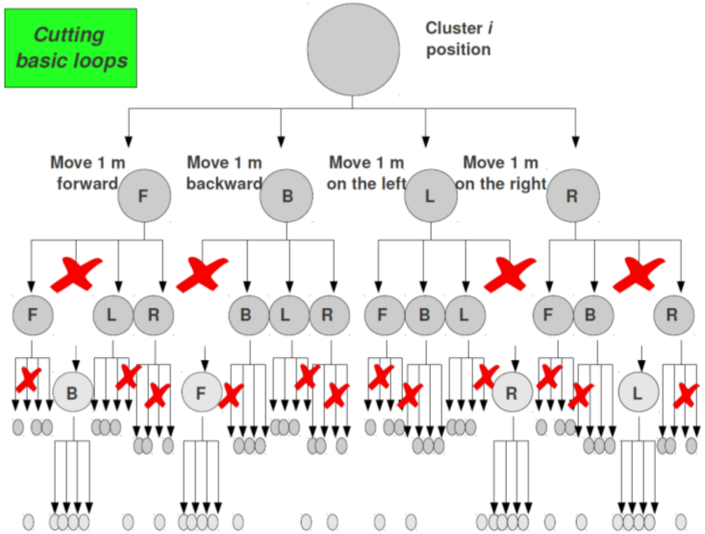
Usually when the particles can be grouped in >1 cluster
Goal: arrive to 1 cluster

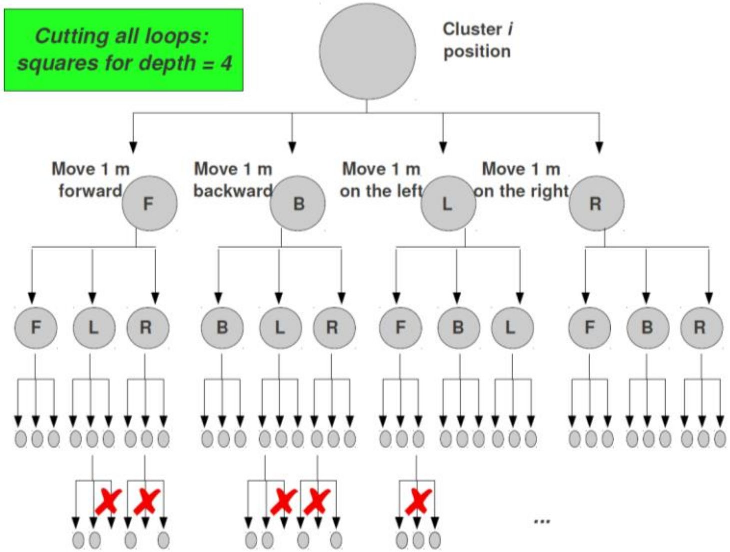
Active Localisation

build a tree-style trajectory, composed by n basic moves, applied to each cluster
For each node, evaluate the benefits and the costs associated
End with the most effective trajectory in between a maximum depth of the tree

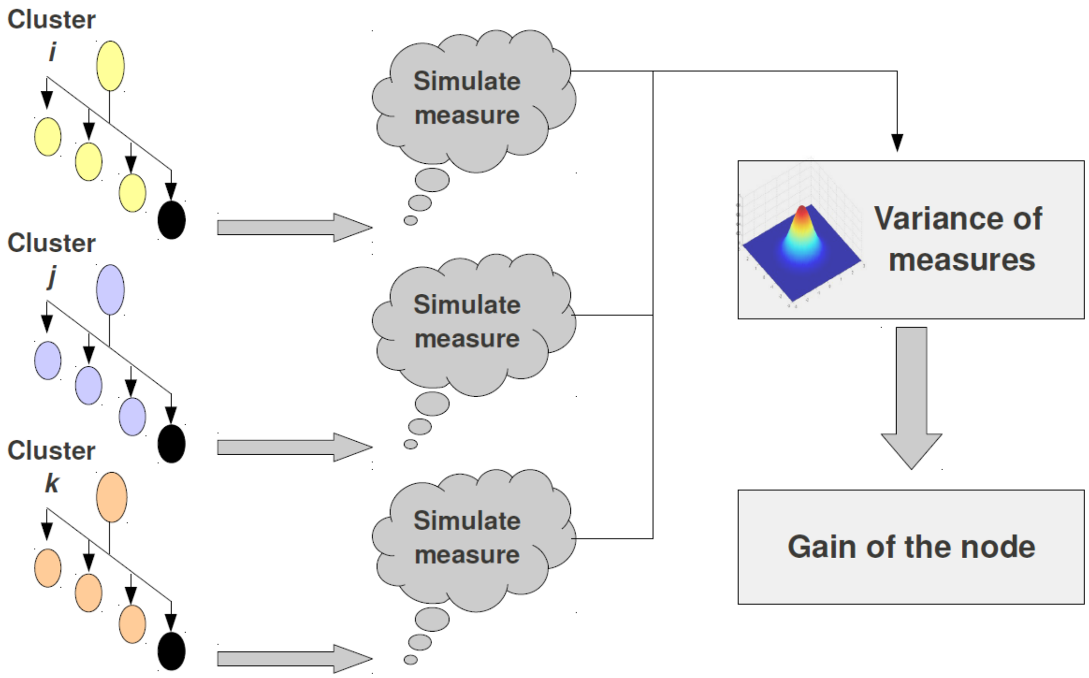


Active Localisation - Optimisations

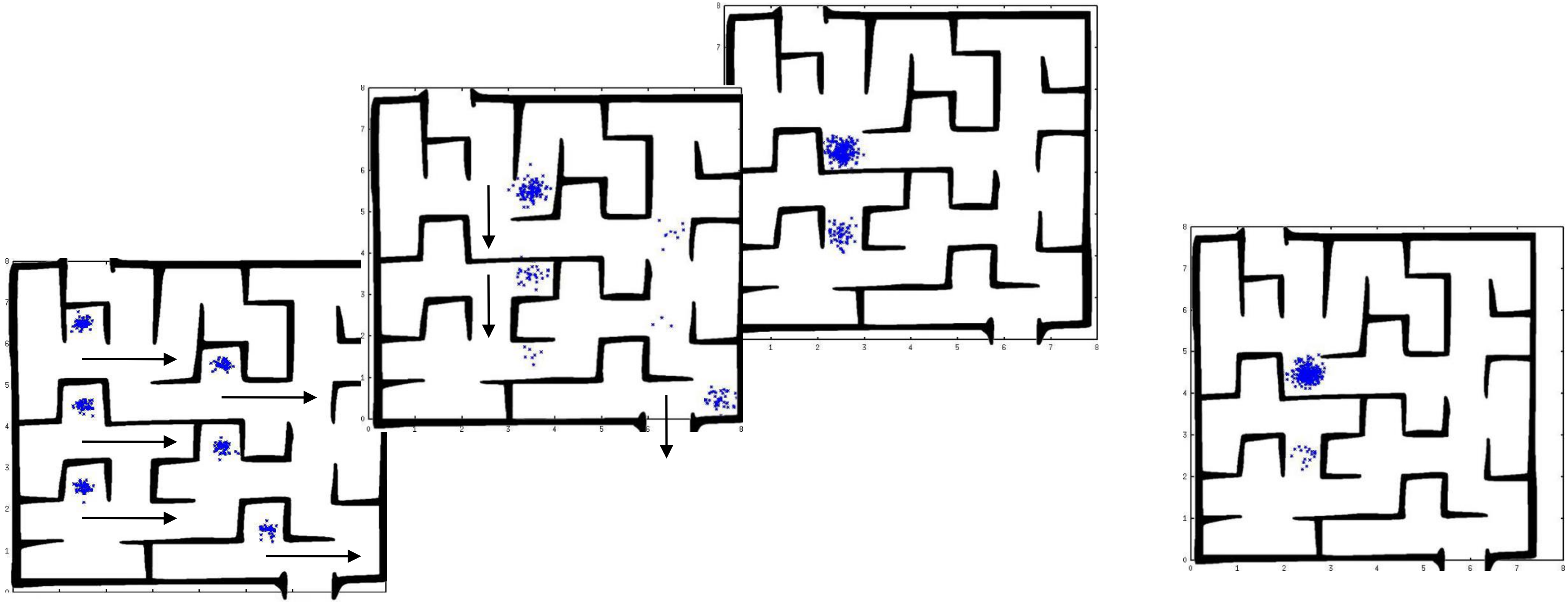




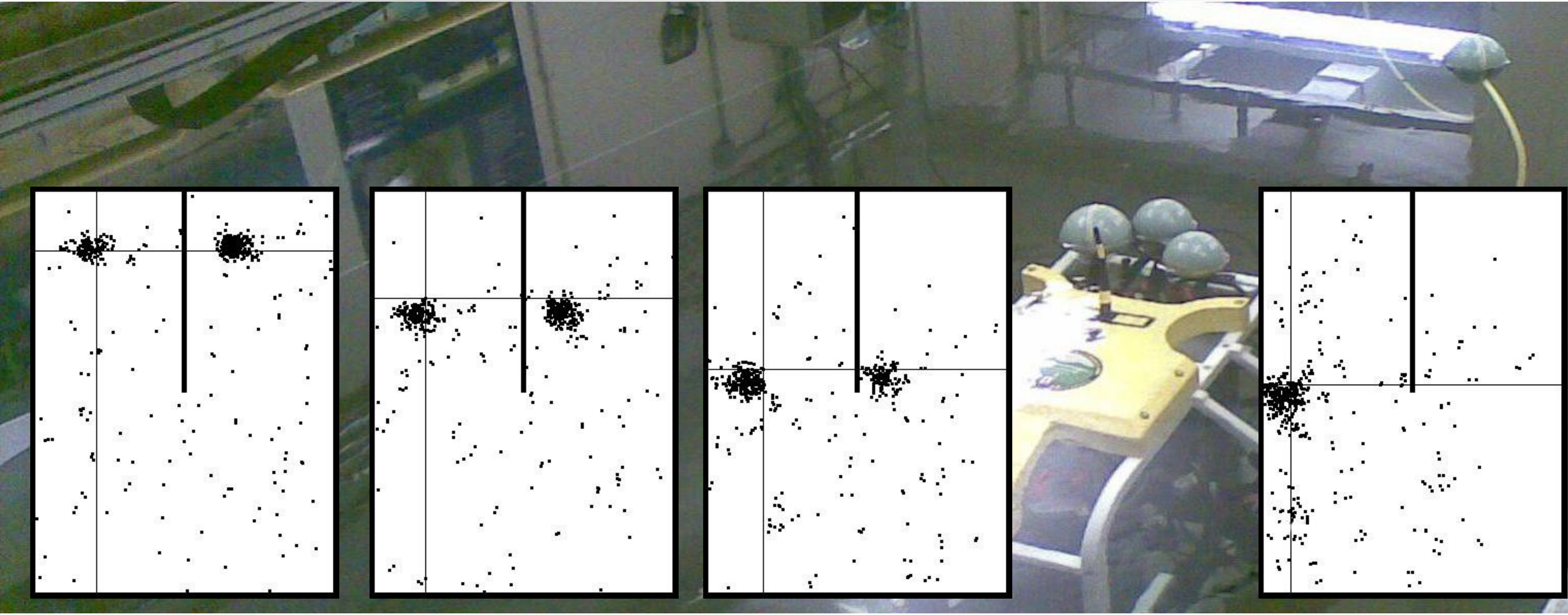
Active Localisation – Gain Calculation



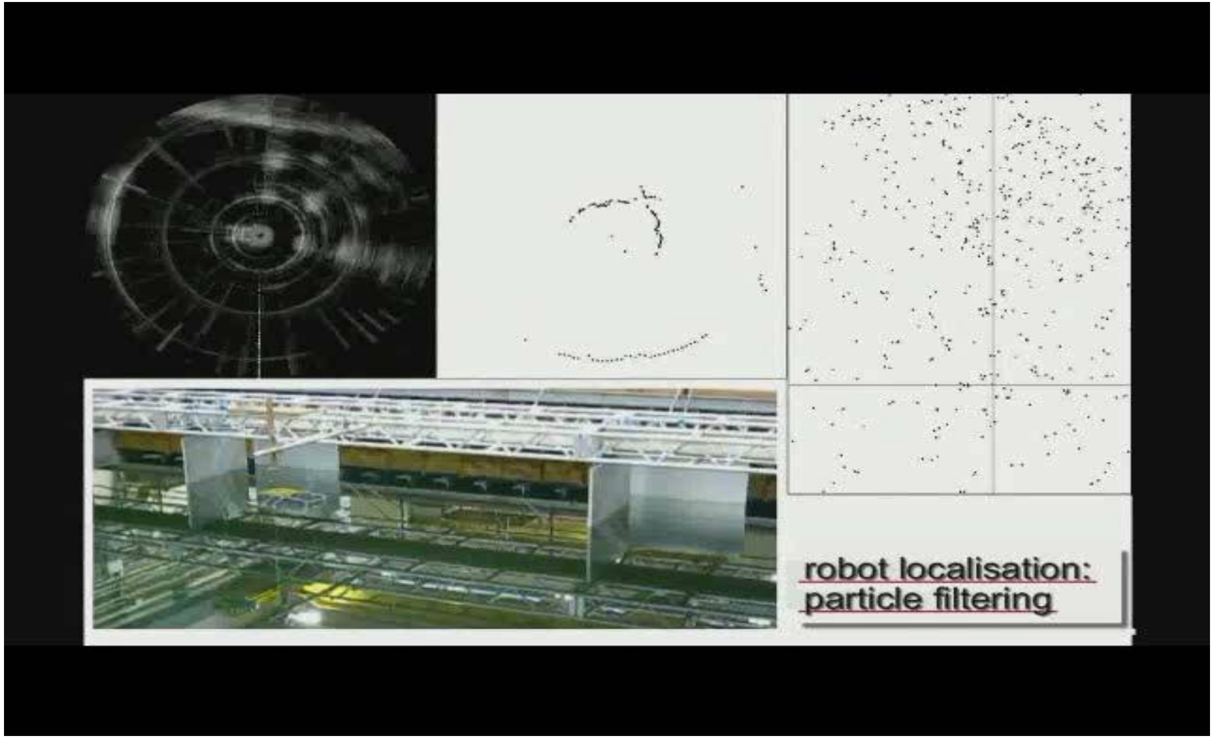
Active Localisation – Simulation Results



Active Localisation – OSL Tank Results

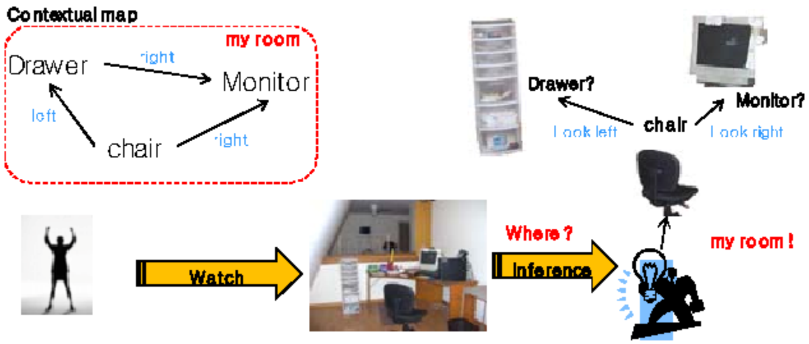


Active Localisation – Wave Tank Results



Semantic information for localisation

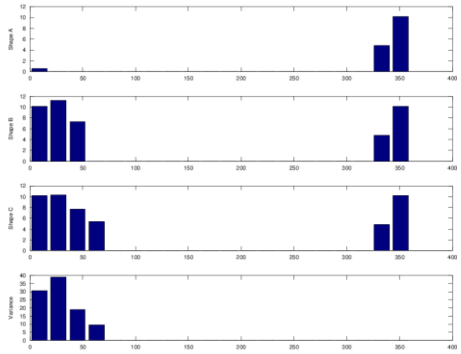
- Semantic localization vs. Semantic-aided localization



- Interested in geometric information about location
- Use of semantic information about the environment

Particle Filters for Semantic Maps

- Sampling → Importance Weighting → Re-sampling
- **Importance Weighting**: how similar is the particle's observation vs. the robot's observation?
- Array of distances → compare index by index



Objects / Symbols?

→ two families of Gaussians

distance, angle

Adjustment weight based on scene similarity

Francesco Maurelli, Szymon Krupinski, **A semantic-aided particle filter approach for AUV localisation**; IEEE Oceans'18, Kobe, Japan

Particle Filters & Semantic: a promising approach

- Adaptation of Particle Filters to include semantic information
- Preliminary results show a slight decrease of error
- Preliminary results show a high improvement in performances (1:6)

Avg. time (ns) - 100 runs	
Semantic-aided	Geometric
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Current / Future Work

- 3D environments: *no big difference in the approach, computational intensive*
- Work with probabilistic maps: *need for a more complete probabilistic framework*
- Work with relations: *currently low-priority*
- Use semantic information for active localisation

What about Autonomous Surface Vessels?

Surface applications

the use of GPS is common: “cheap”, accurate and increasingly reliable

… but because of this, often it is the **only** sensor dedicated to positioning.

Urban Scenario

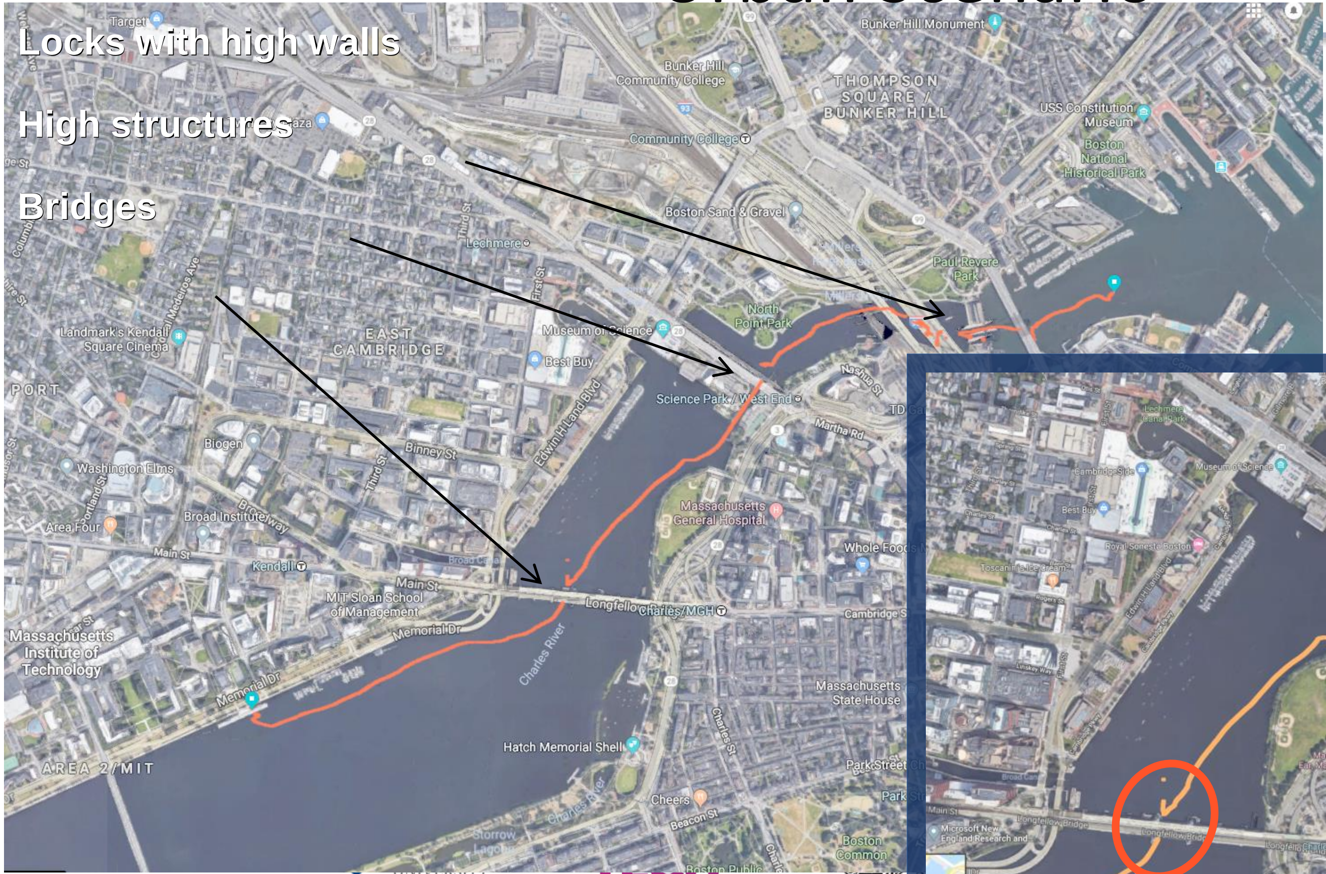
3D data gathering in a harbor/river environment

surrounded by buildings
crossed by bridges

Applications:

Patrolling, river debris cleanup
Survey
Autonomous coastal ship or ferry
Autonomous river taxi (e.g. SeaBubbles – undergoing tests in Paris, France)

Urban Scenario



GPS-only results:

“holes” in trajectory

false segments due to multipath

Urban Scenario

Sensors

Principal sensor: 360° laser scanner (Velodyne 32E)

Laser scanner are slowly making their way into the underwater domain

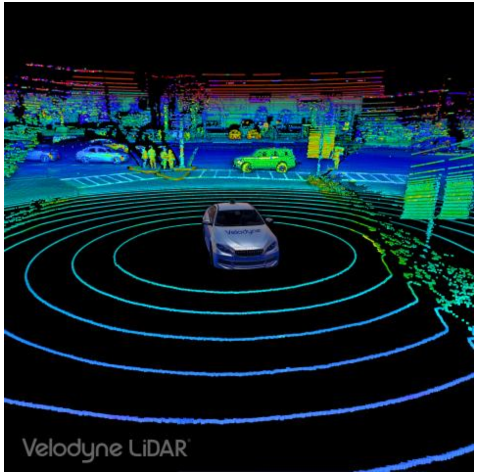
- Seavision / Kraken Robotik
- MxxxUW series / Newton
- SL3 / 3D@depth
- …

Autonomous Driving vs Autonomous Cruising

Water surface does not typically produce reflections (many processing algorithms rely on the presence of "ground plane")

World Objects typically far away – the clouds are sparse

Motions due to roll and pitch must be factored in



GPS Trouble

GPS broadcasts at 1.2 – 1.5 GHz frequency. Principle sources of errors:

- reflections of the signal that reaches the receiver (multipath)
- atmospheric distortion

Using the L5 band (slowly coming to market), theoretical accuracy of 30 cm can be achieved

Horizontal Dilution of Precision (HDOP) gives estimate of the of the current precision due to satellite position and condition

Errors sometimes hard to detect, especially in the multipath scenario

Scan Matching

Align two sets of partially overlapping 3-D point clouds

– Output: full 6 d.o.f. rotation + translation

Great results obtained in **indoor robotics** as SLAM component

Technique applied to **underwater positioning**
– Ribas 2008 (mechanically scanning sonar, SLAM)
– Maurelli 2009 (horizontal sonar scans, particle filter-based positioning)
– Man-made, cluttered environment is actually an advantage

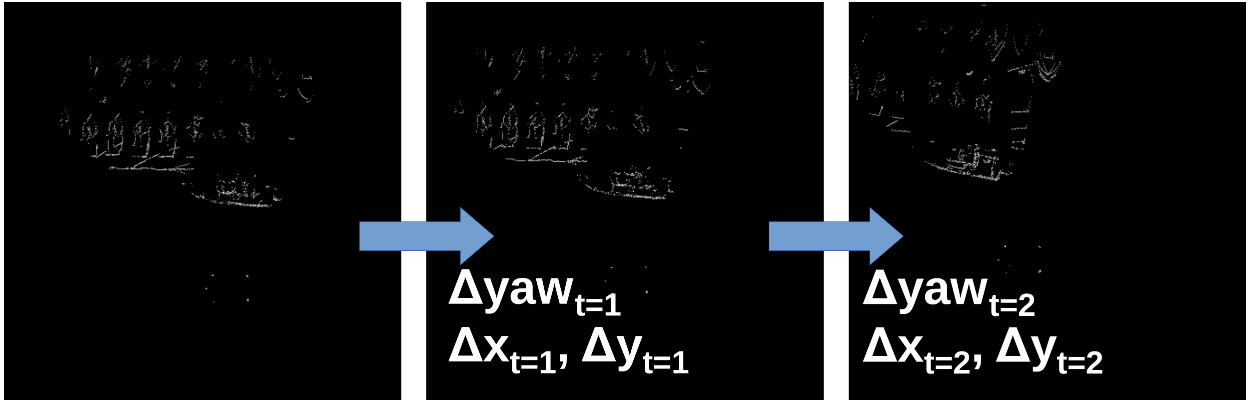
Provides **reference features**

Scan Matching

Further adjustment to the "marine" problem

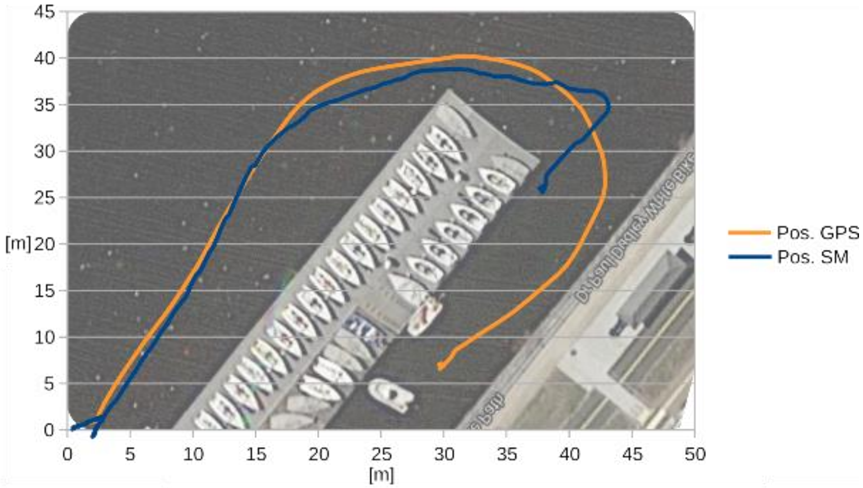
We are mostly interested in a 2-D situation (yaw change + displacement)

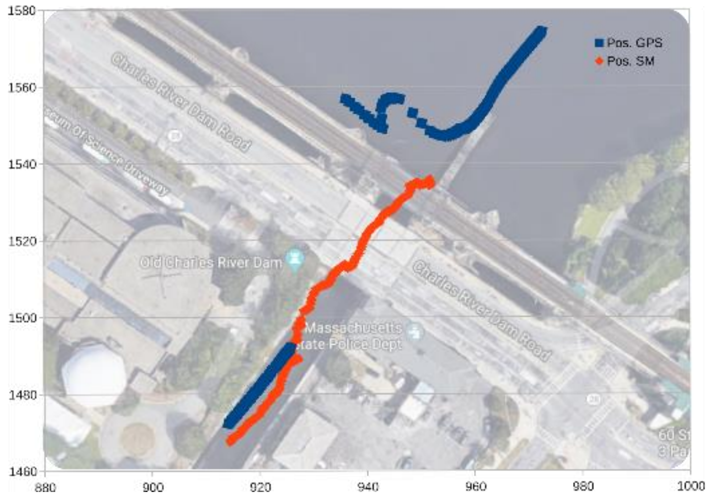
Point clouds can be reduced to projections of specified resolution and size
→ better guarantee of computational complexity



This technique can be used on imaging sonar output without much modification!

Scan Matching – preliminary field results





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Szymon Krupinski, Francesco Maurelli, **Positioning aiding using LiDAR in GPS signal loss scenarios**; IEEE USYS'18, Wuhan, China

QUESTIONS ?