# Autonomous Lifelong Navigation, Experiment Replication and Benchmarking

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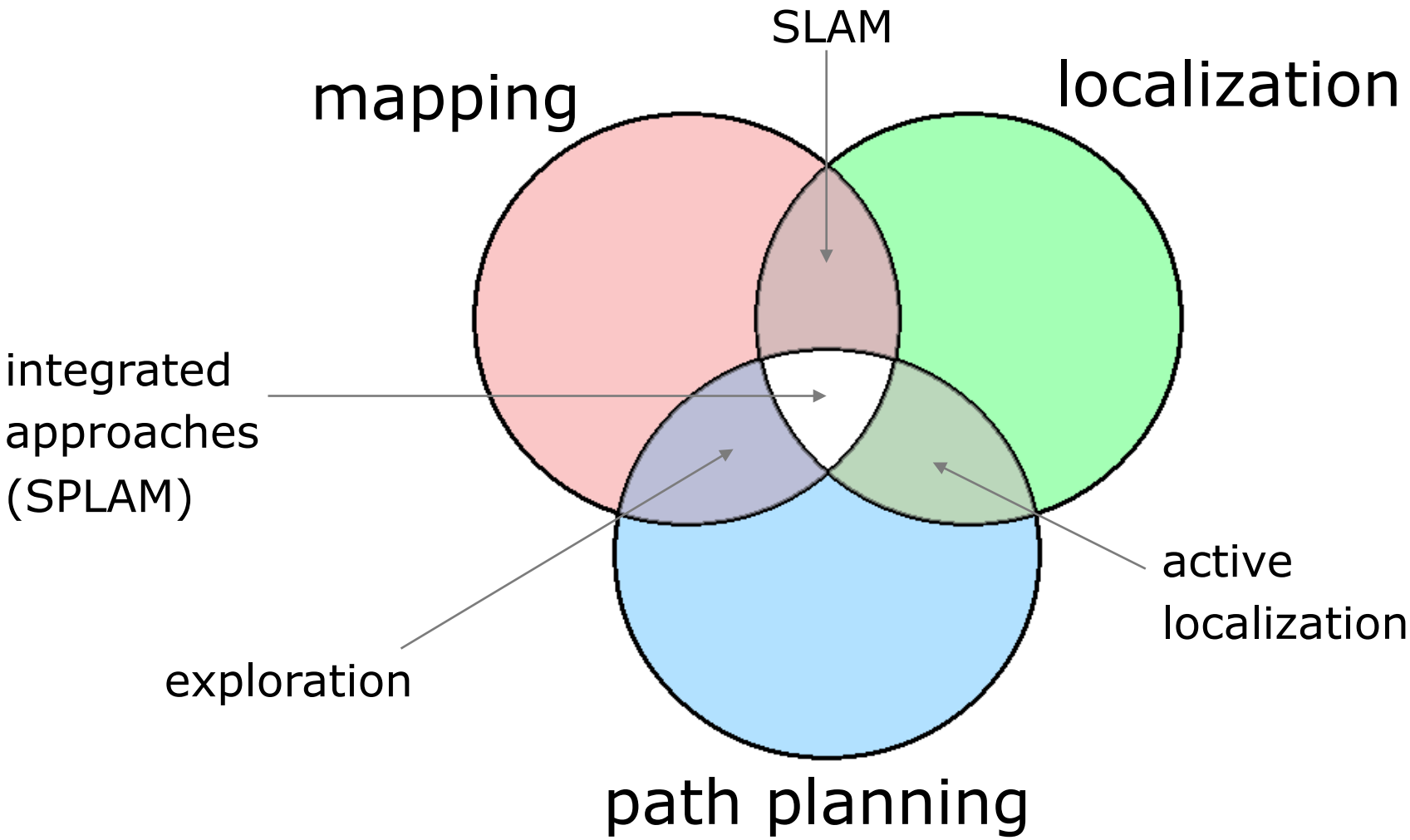
# Motivation

- No gold standard to evaluate and compare the results of navigation systems

- Many measures can characterize a navigation system, for instance: position accuracy (local), execution time, energy efficiency.

- However,
  - A navigation system is a closed-loop-system,
  - the actions taken influence the next observations, and
  - a **complete** system can be evaluated only by either real-world experiments, or by using highly accurate simulators.

# Taxonomy of Navigation



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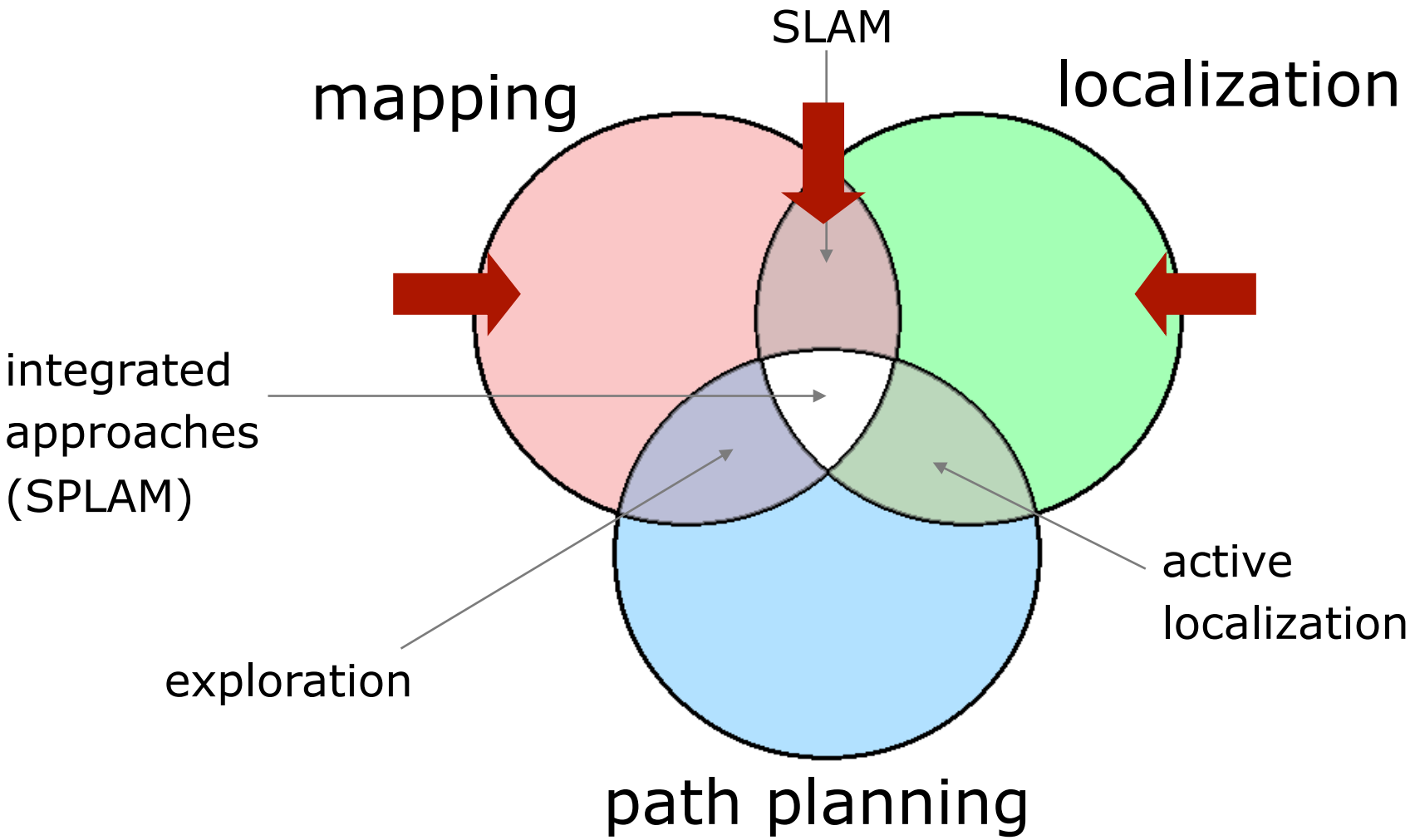

# Related Work

- SLAM approaches
  (Smith&Cheeseman, Lu&Milios, Frese, Duckett et al., Dissanayake et al., Howard et al., Eustice et al., Grisetti et al., Stachniss et al., Olson, …)

- Competitions
  (DGC, RoboCup, NIST, …)

- Data repositories
  (Radish, RAWSEEDS, OpenSLAM, …)

# Benchmarking Lifelong Perception for Navigation

- The datasets for comparison can be arbitrary large
  - Use realistic simulators to produce these datasets
  - **Generate realistic long datasets by combining real data**
- The algorithms should cope with additional issues:
  - Changes in the environment
  - Impossibility to store all data of the robot

# Measures

- Uncertainty
  (Entropy, KL-Divergence, …)

- Variance of estimators
  (Cramer-Rao-bound, Fisher information, …)

- Quality of estimates
  (observation likelihood, normalized estimation error squared, distance of relative observations, …)

# Practical Applications

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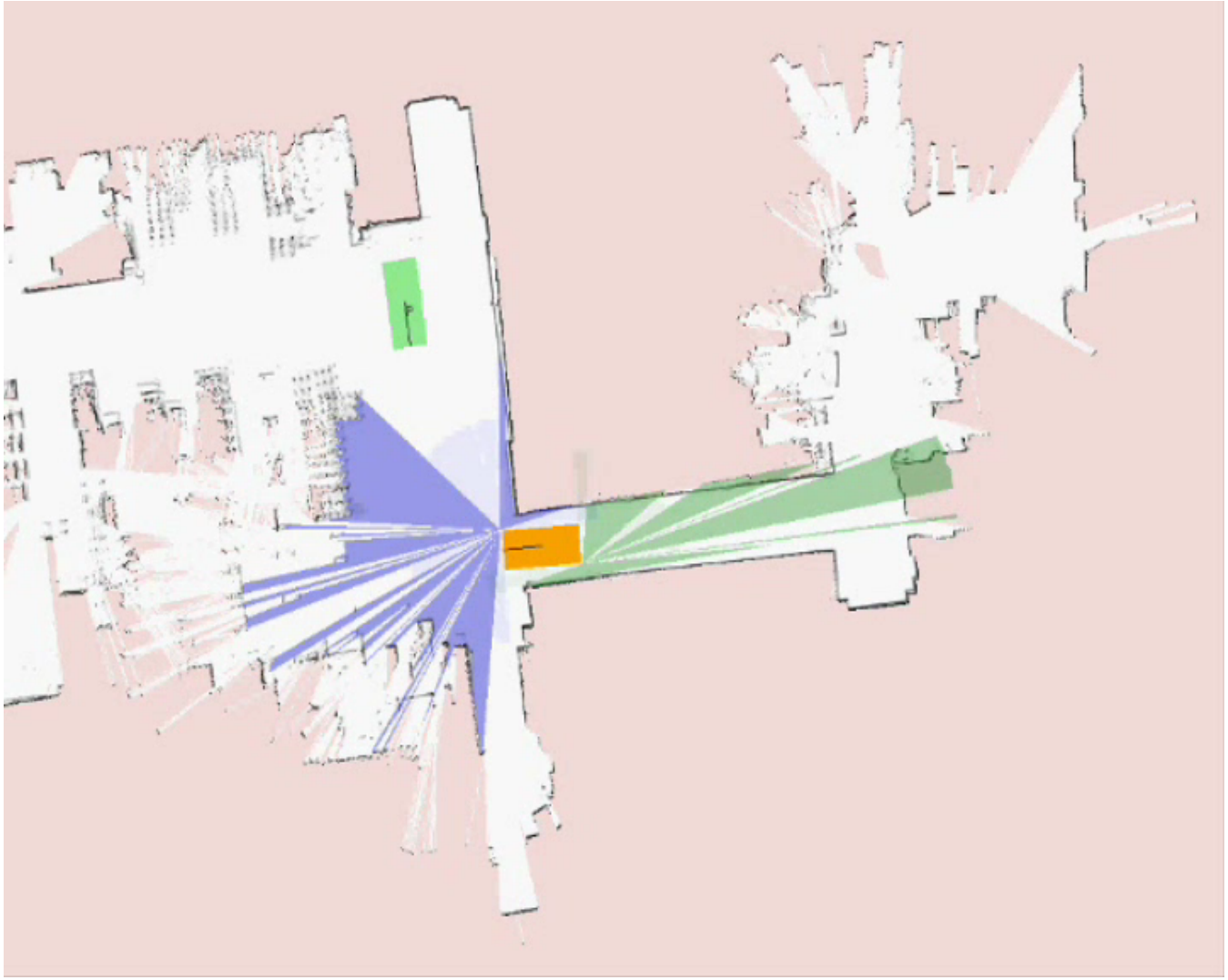


# Benchmarking Perception for Navigation

- The robot should be accurately localized in its local surrounding
- The map should be topologically consistent
- The reaction times (latency) should be small enough to prevent collisions

- The robot should be maximally successful!

# Questions?

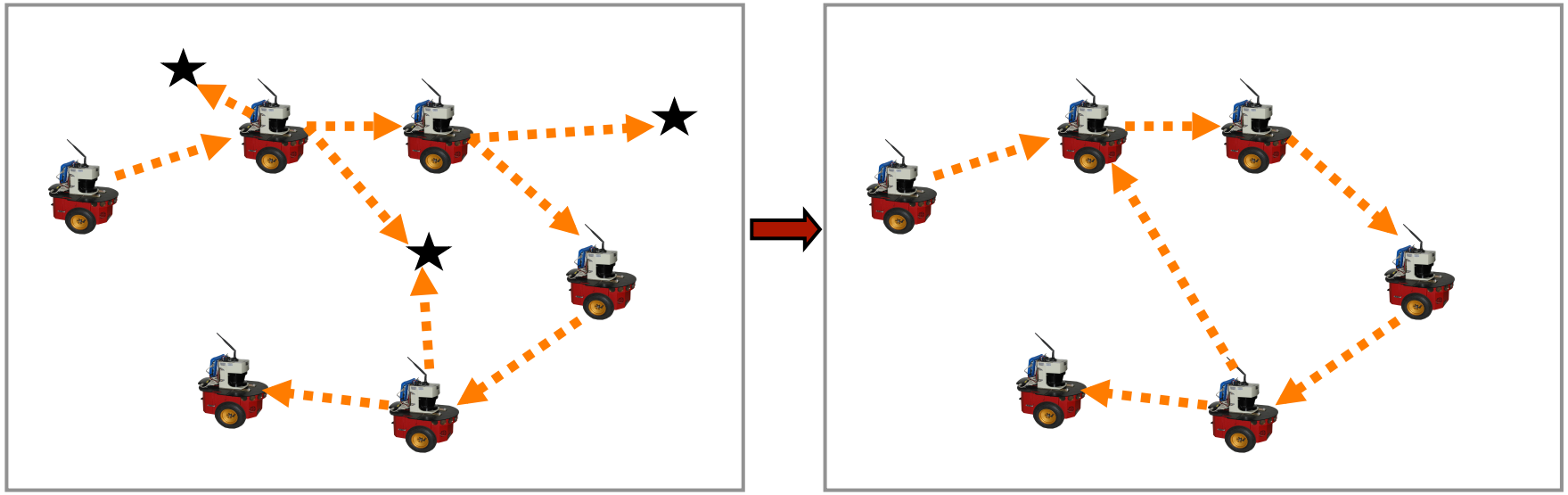
- How to measure the local consistency?
  - should be sensor independent
- How to generate arbitrary long sequences from real world data such that the local consistency of a SLAM method can be measured?
  - should minimize the human effort
  - should minimize the data to be transmitted
  - should encode the ground truth

# What do we get from SLAM?

- All SLAM approaches are at least able to estimate the current robot position $\boldsymbol{x}_t$
- Smoothing approaches estimate the trajectory $\boldsymbol{x}_{0:t}$
- Classical filtering approaches estimate only the map (landmark positions) $\boldsymbol{l}_{0:k}$
- The two representations are dual:
  - From the map one can recover the trajectory by localization
  - From the trajectory one can recover the map via mapping with known poses.
- We focus on the robot's trajectory because it is sensor independent and directly relates to the localization accuracy

# Pose Graph

- A pose graph encodes the poses of the robot during mapping as well as constraints resulting from observations.
- It is independent of the kind of observations
- and the type of the map (landmarks, grids, …).



Robot poses and observations

Pose graph

# Our Approach

- measures the relative errors between nearby poses

$$\mathbf{e}_{i,j} = (\mathbf{x}_j \ominus \mathbf{x}_i) \ominus \delta^*_{i,j}$$

estimated relative movement

ground truth

- which is exactly what approaches to graph-based SLAM seek to minimize.

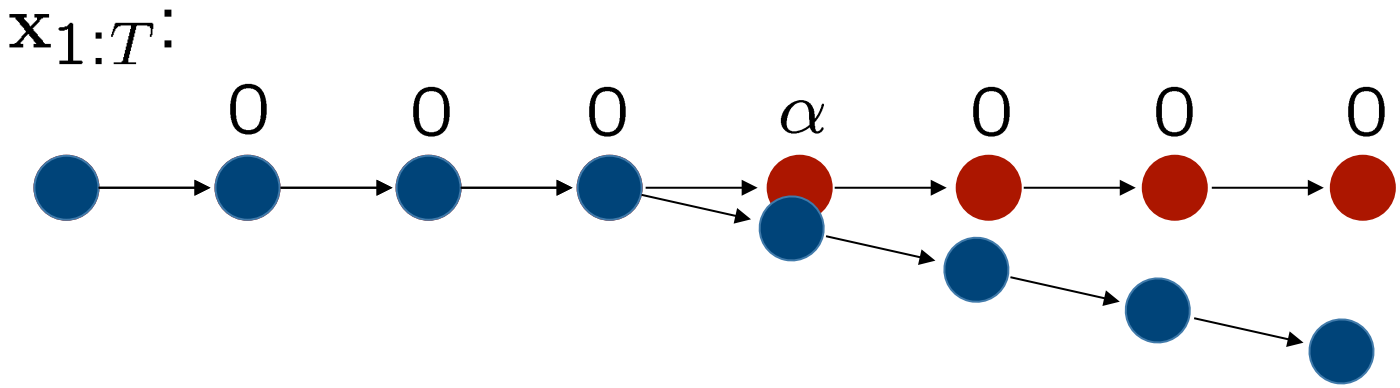
# Metric Based on Relative Poses

$$\varepsilon(\delta) = \frac{1}{N} \sum_{i,j} \mathbf{e}_{i,j}^T \boldsymbol{\Omega}_{i,j} \mathbf{e}_{i,j}$$

Uncertainty of the ground truth

- Which is the Chi-square error of the trajectory w.r.t. the ground truth measurements.

# Application to the Example



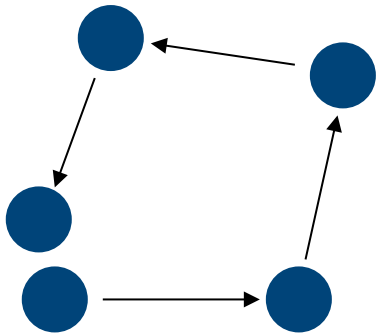

$$\varepsilon(\mathbf{x}_{1:T}) = \alpha$$

- The one localization error weighs exactly $\alpha$ in the metric. Errors between poses that are far apart appear less since they do not cause localization problems.

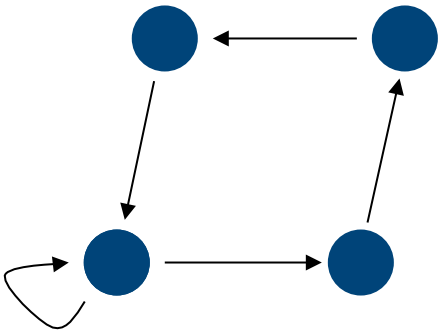
$$\Omega_* = \mathbf{I}$$

# Selection of Relations

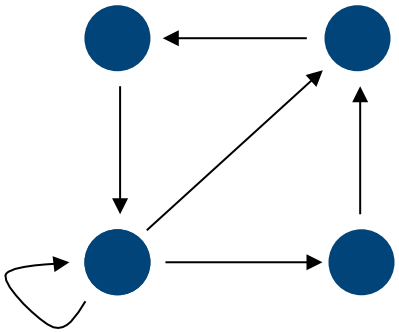
- No loop closure links:
  local consistency only
  (wrt. time)



- Loop closure links:
  local consistency
  (wrt. space)



- Links between far
  away nodes:
  global consistency

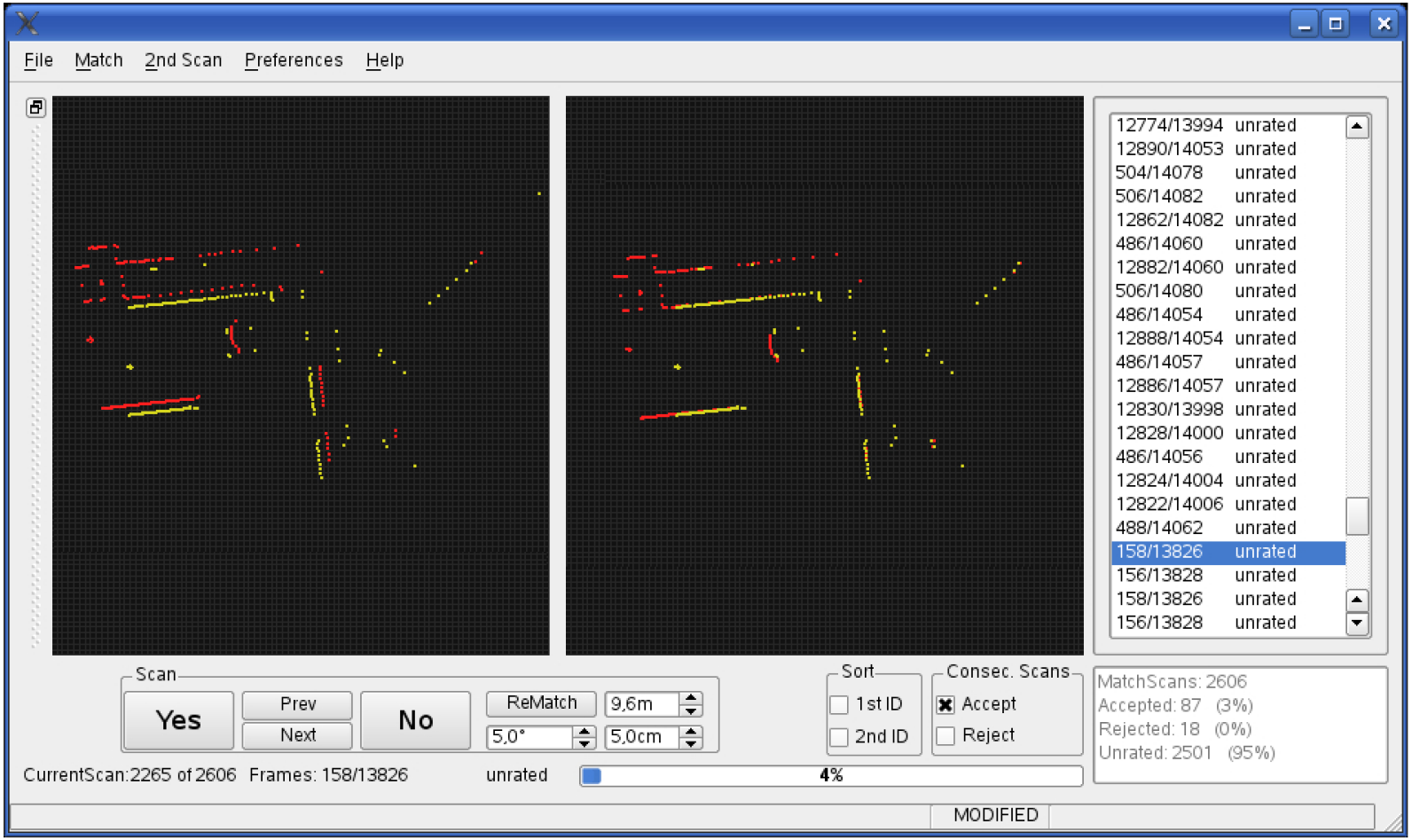


# Obtaining Ground Truth Relations

- Besides in simulation, true relations are hard to obtain
- Highly accurate measurement device (e.g., Simeo positioning system or any other sources)
- How can we use existing datasets for evaluations (Intel Research, MIT infinite corridor, …)?
- For laser-based SLAM, perform scan alignment paired with manual inspection

# Graphical Interface to Confirm & Correct Constraints

- Scan alignment paired with manual inspection to generate close to ground truth relations



# Arbitrary Long Real World Datasets

- It is impossible to have a robot running forever
- The sequence of data needs to capture the relevant aspects of the phenomenon
  - Temporal changes:
    - day/night transition
    - moving objects
    - changes in the structure
- Obtaining ground truth should be as easy as possible
- Using **real world data**

# Acquiring the Initial Data

- Select a (large) set of positions in the environment, potentially marking them with a unique landmark (e.g., based on RFID).

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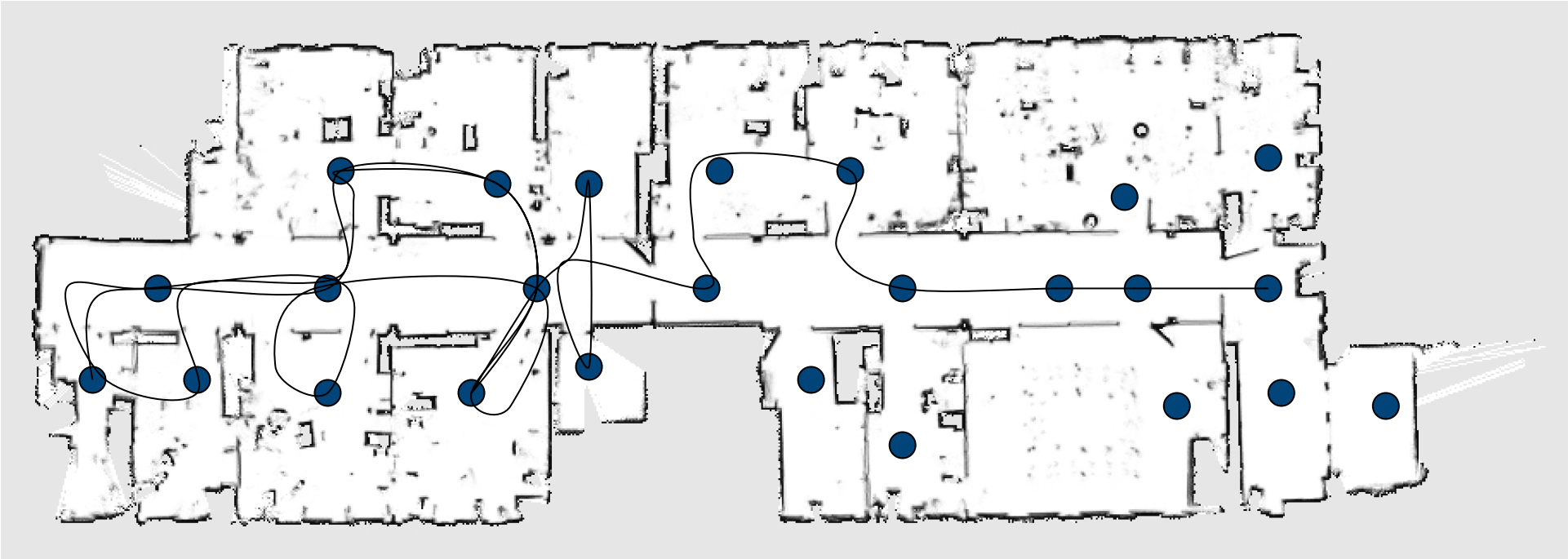

- Select a (large) set of positions in the environment, potentially marking them with a unique landmark (e.g., based on RFID).
- Acquire a set of datasets during several periods of the day.
- All datasets should **start** and **end** from one of the chosen positions, and traverse as many as possible.

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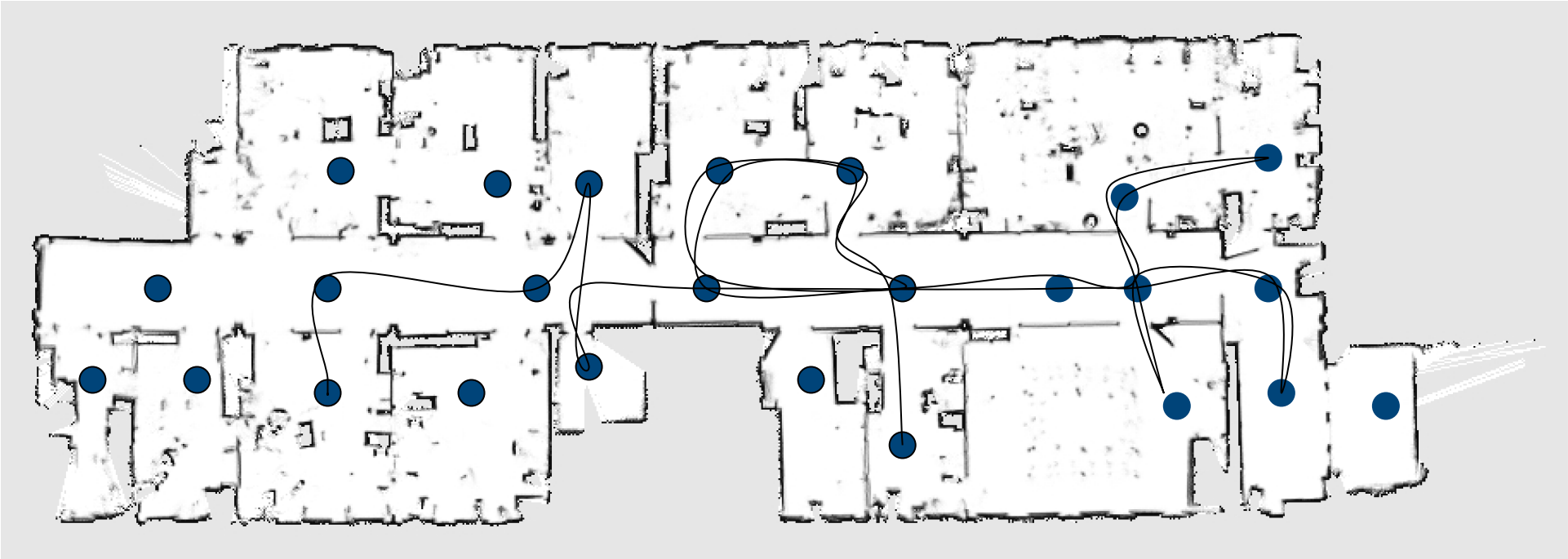

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- Doing the manual alignment for each pair of nearby nodes has a cost up to O(N^2), where N is total length of all trajectories

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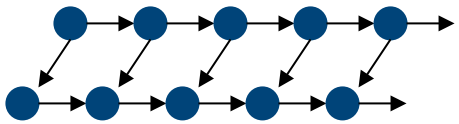

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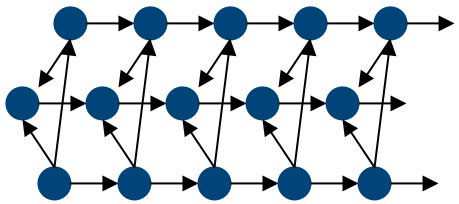

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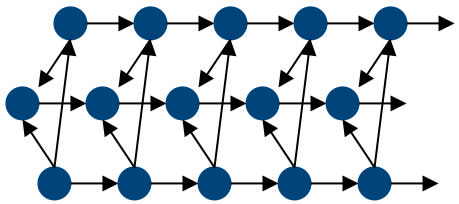

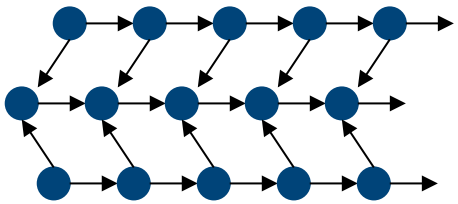

- Doing the manual alignment for each pair of nearby nodes has a cost up to O(N^2), where N is total length of all trajectories
- In fact this can be reduced to a cost more or less linear by
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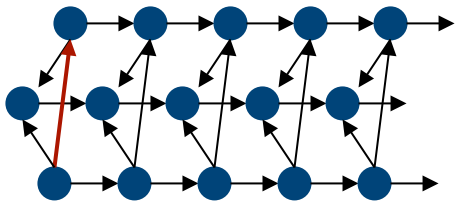

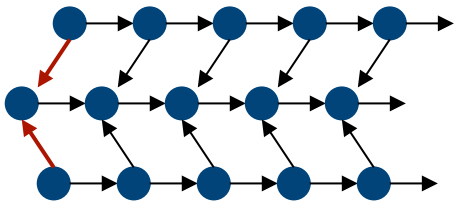

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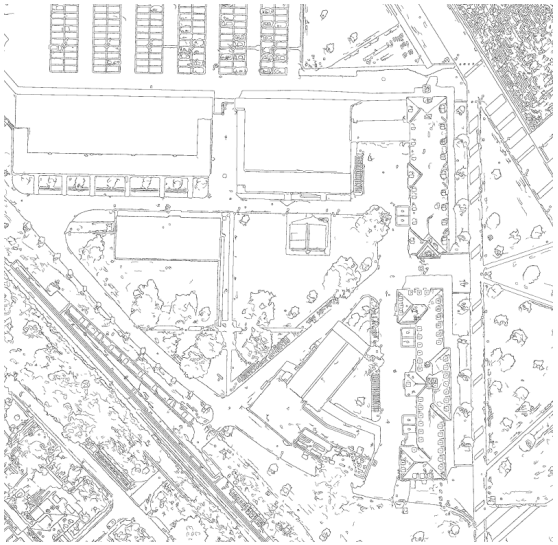
- In fact this can be reduced to a cost more or less linear by
  - Inserting a constraint in a region only between the current node and the oldest one in that region.
  - All other constraints can be obtained by chaining pairs of measurements.
- **Still a lot of work but more feasible**

# What Else?

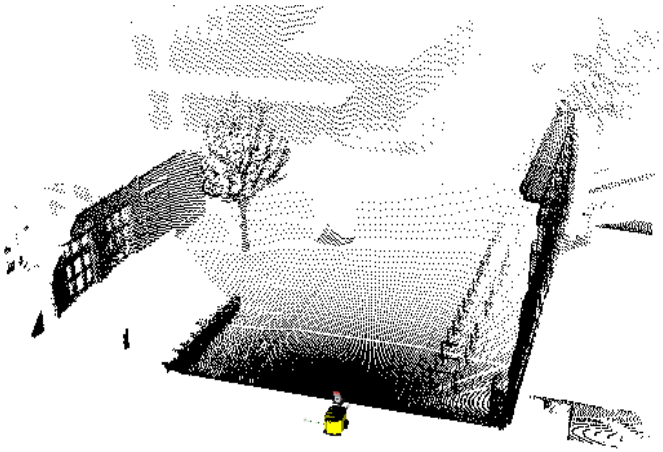
- Statistical tests: Does the algorithm yield a significant improvement over the state of the art?
- Such tests are typically based on a large number of data.
- How can we do this in a life-long setting?

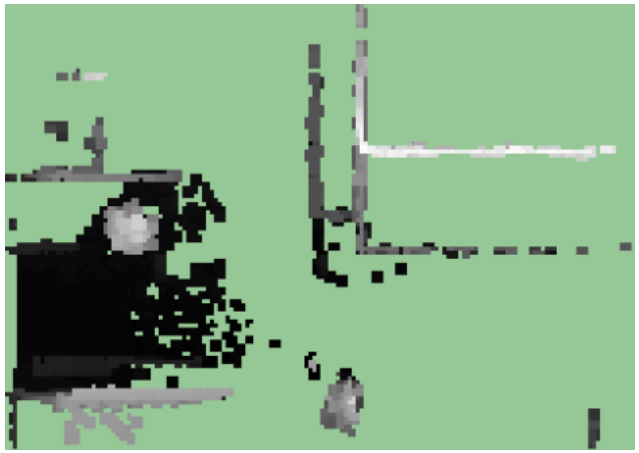
# SLAM using Aerial Images

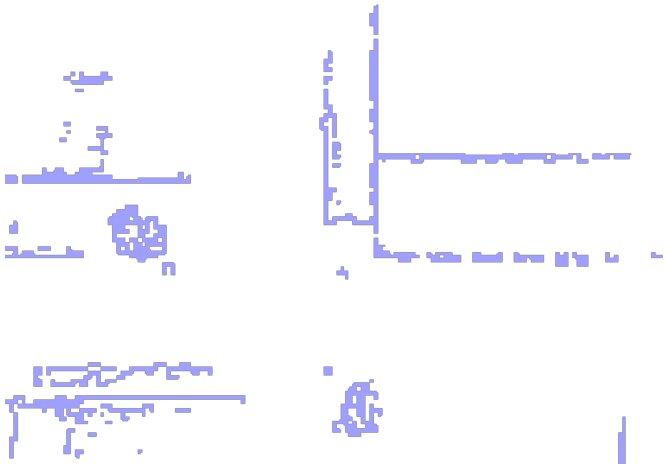
- Changes in color often occur at height variations.
- Canny edge extraction to get a likelihood field.
- Consider different view-points of the wheel-based robot and the aerial image.



# Processing the Sensor Data





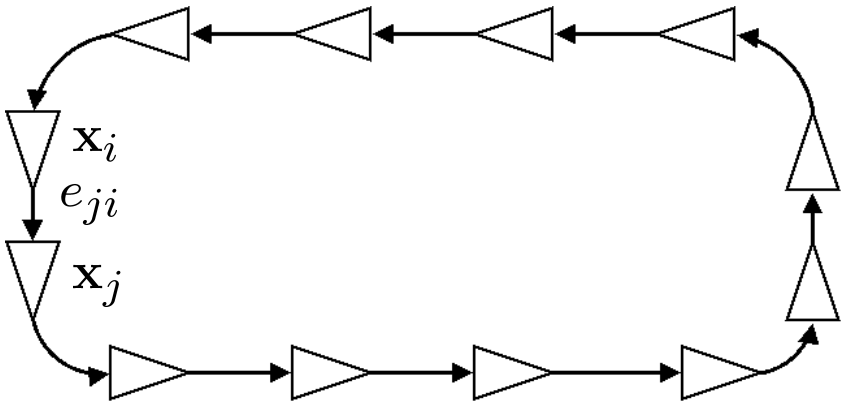


3D range data
Compute the z-buffer
from top
Detect large variations
in height

# Graph-SLAM

- Use a graph structure to represent the SLAM problem.
- Poses as nodes, spatial constraints between the poses as edges.

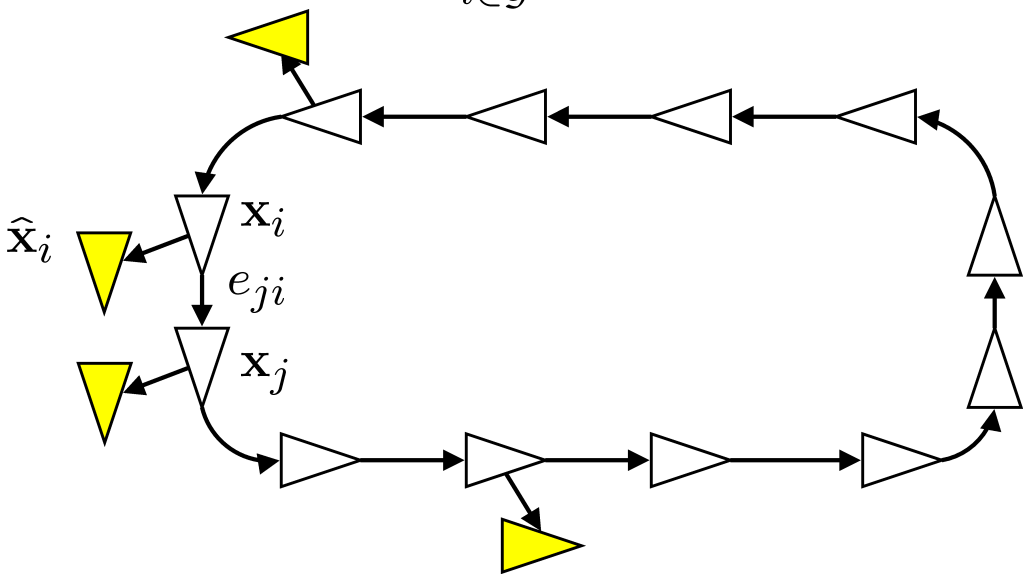
$$(\mathbf{x}_1, \ldots, \mathbf{x}_n)^* = \underset{(\mathbf{x}_1,\ldots,\mathbf{x}_n)}{\text{argmin}} \sum_{\langle j,i \rangle} e_{ji}(\mathbf{x}_i, \mathbf{x}_j)^T \Omega_{ji} e_{ji}(\mathbf{x}_i, \mathbf{x}_j)$$



# Graph-SLAM with Prior

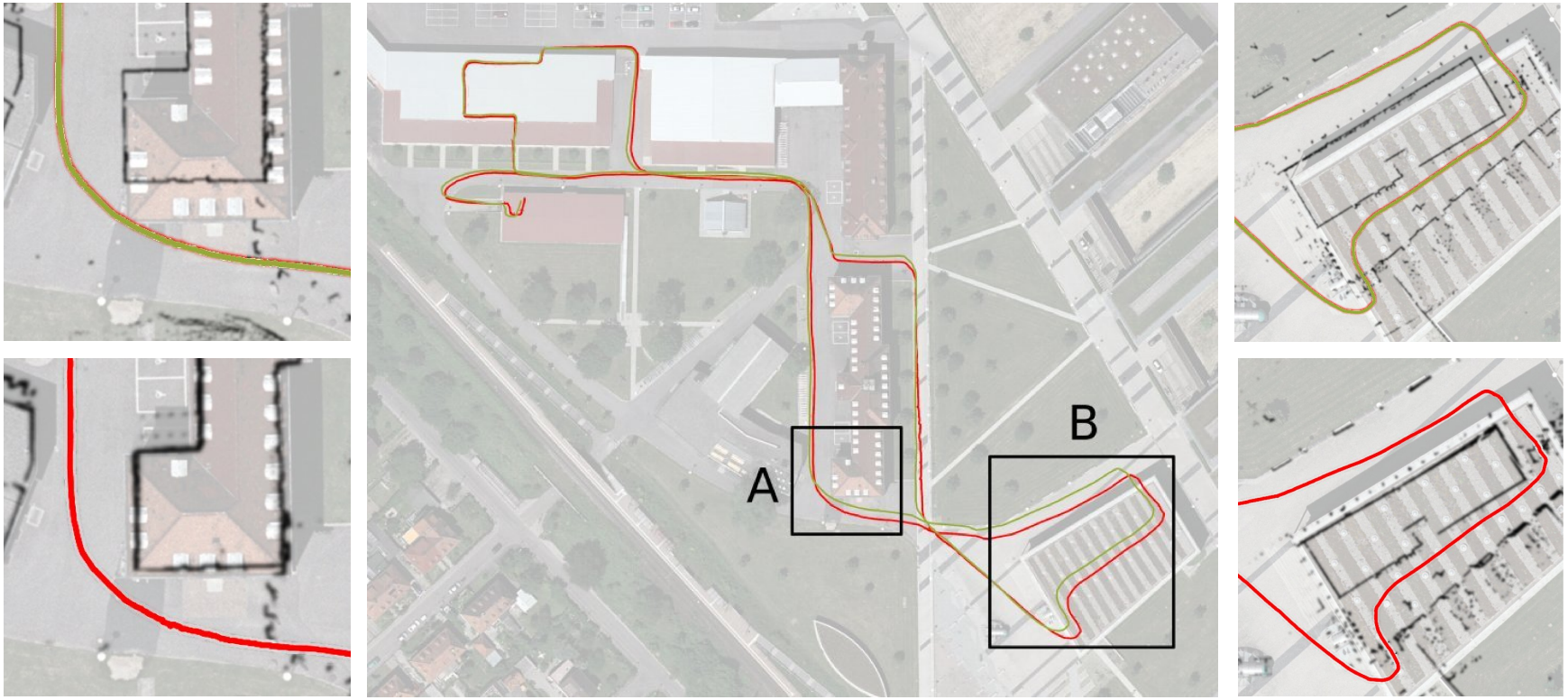
- Integrate the prior into graph-SLAM

$$(\mathbf{x}_1, \ldots, \mathbf{x}_n)^* = \underset{(\mathbf{x}_1,\ldots,\mathbf{x}_n)}{\text{argmin}} \sum_{\langle j,i \rangle} e_{ji}(\mathbf{x}_i, \mathbf{x}_j)^T \Omega_{ji} e_{ji}(\mathbf{x}_i, \mathbf{x}_j) + \sum_{i \in \mathcal{G}} (\mathbf{x}_i - \hat{\mathbf{x}}_i)^T R_i (\mathbf{x}_i - \hat{\mathbf{x}}_i)$$




- Optimization carried out based on non-linear conjugate gradients

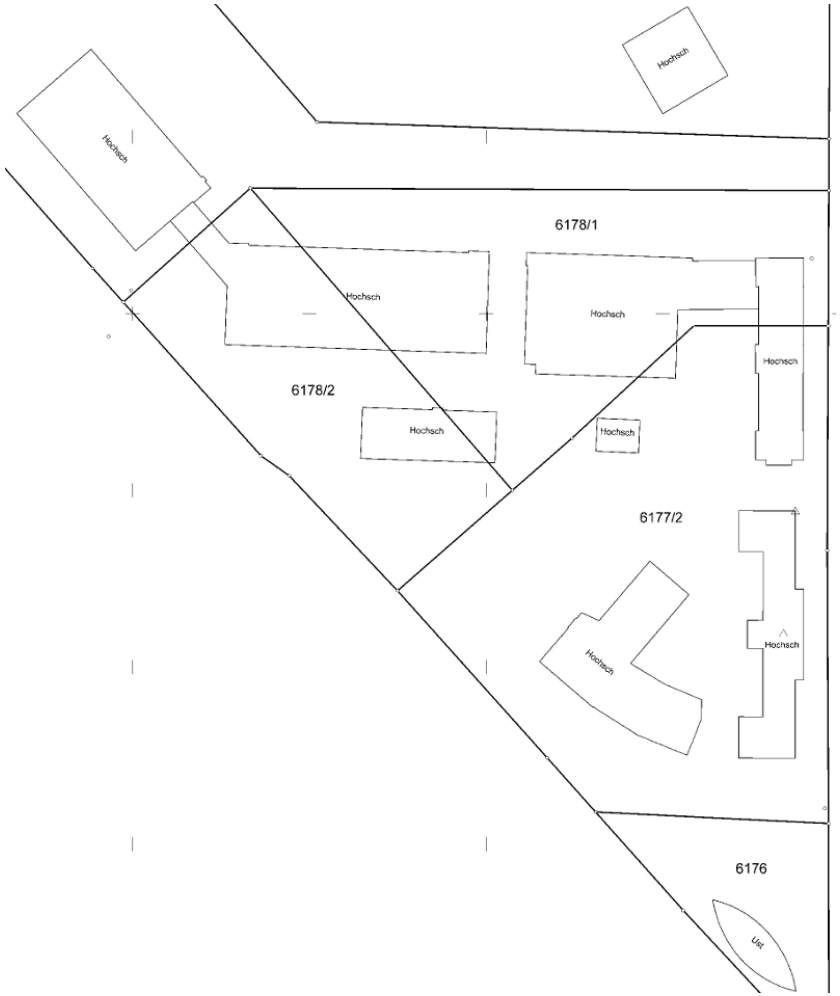
# Global Map Accuracy




**By exploiting the prior information, we achieve a better global consistency.**

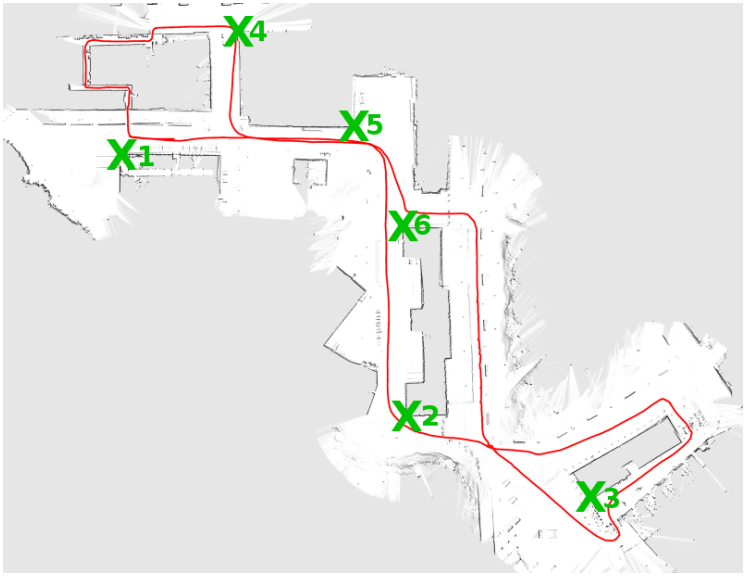
# Ground Truth Data

- Survey data provided by the German Land Registry office
- Outer walls of the buildings in a Gauss-Krüger reference frame

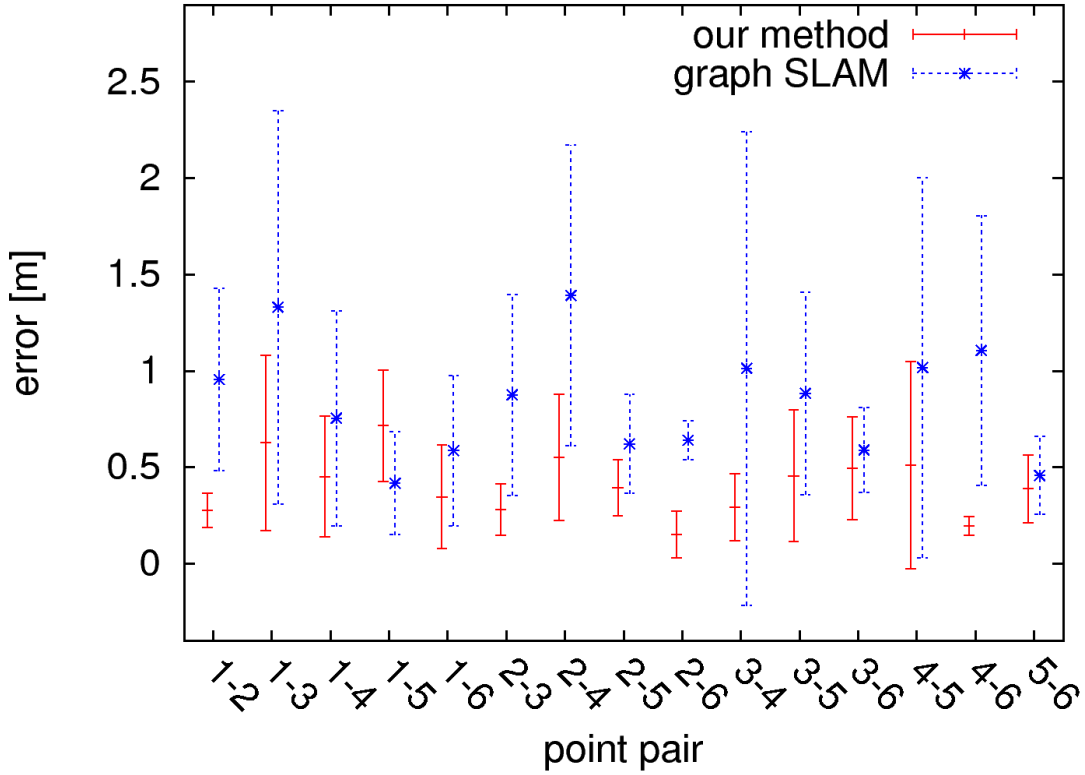


# Statistical Results (1)

- Five data sets.
- We evaluate the pair-wise distance between known points on the map (corners of buildings).



# Statistical Results (2)




- Our method achieves a higher accuracy than graph-SLAM without prior information
- and is more stable.

# Problems

- How to measure the usefulness of a map
- An accurate map might lead to a less efficient behavior than a less accurate map.
- How to benchmark a complete system?

# My Suggestion

- Treat the application as a reinforcement learning problem
- The robot should have the ability to choose between
  - Task execution
  - Localization
  - SLAM actions
- Choosing the optimal trade-off between exploration and exploitation is the key challenge?

# Where will we Arrive at?

- Robotic systems that reliably perform their applications
- We measure them by their performance:
  - What do they cost (also during runtime)?
  - How many tasks did they solve and what was the benefit of this?

# Thanks!