Robotic Mapping into the Fourth Dimension

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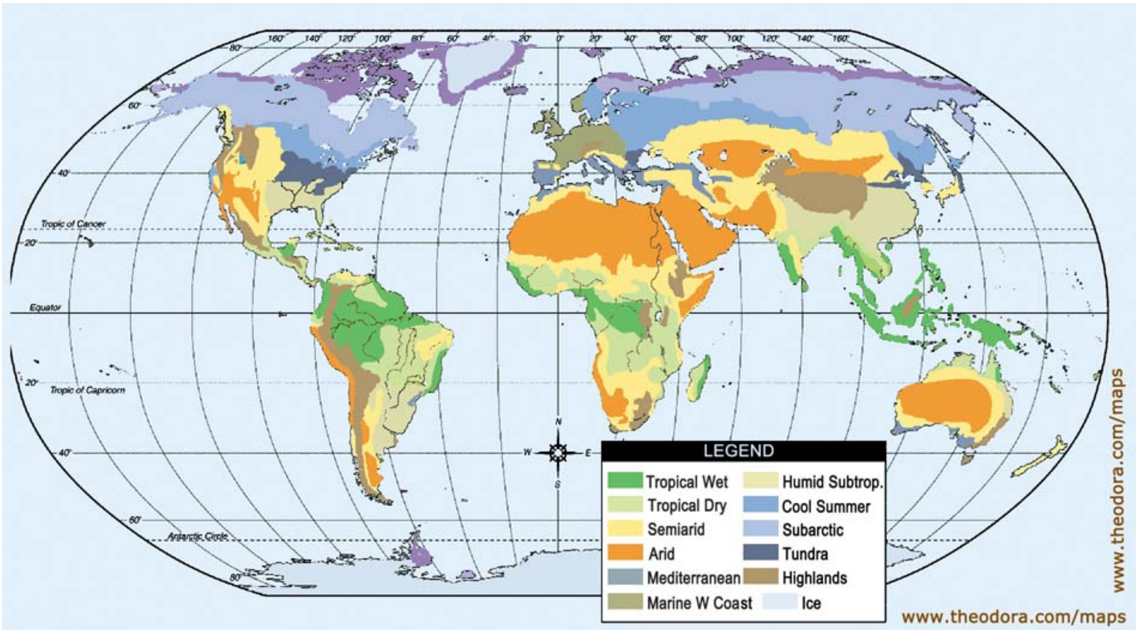
Robotic Mapping into the Fourth Dimension

- Introduction
  - Challenges for Long-Term Mapping
- Mapping & Localisation in Static Environments
- Mapping & Localisation in Changing Environments
  - Dynamic maps
  - Meta-rooms
  - Frequency mapping
- Conclusions

INTRODUCTION

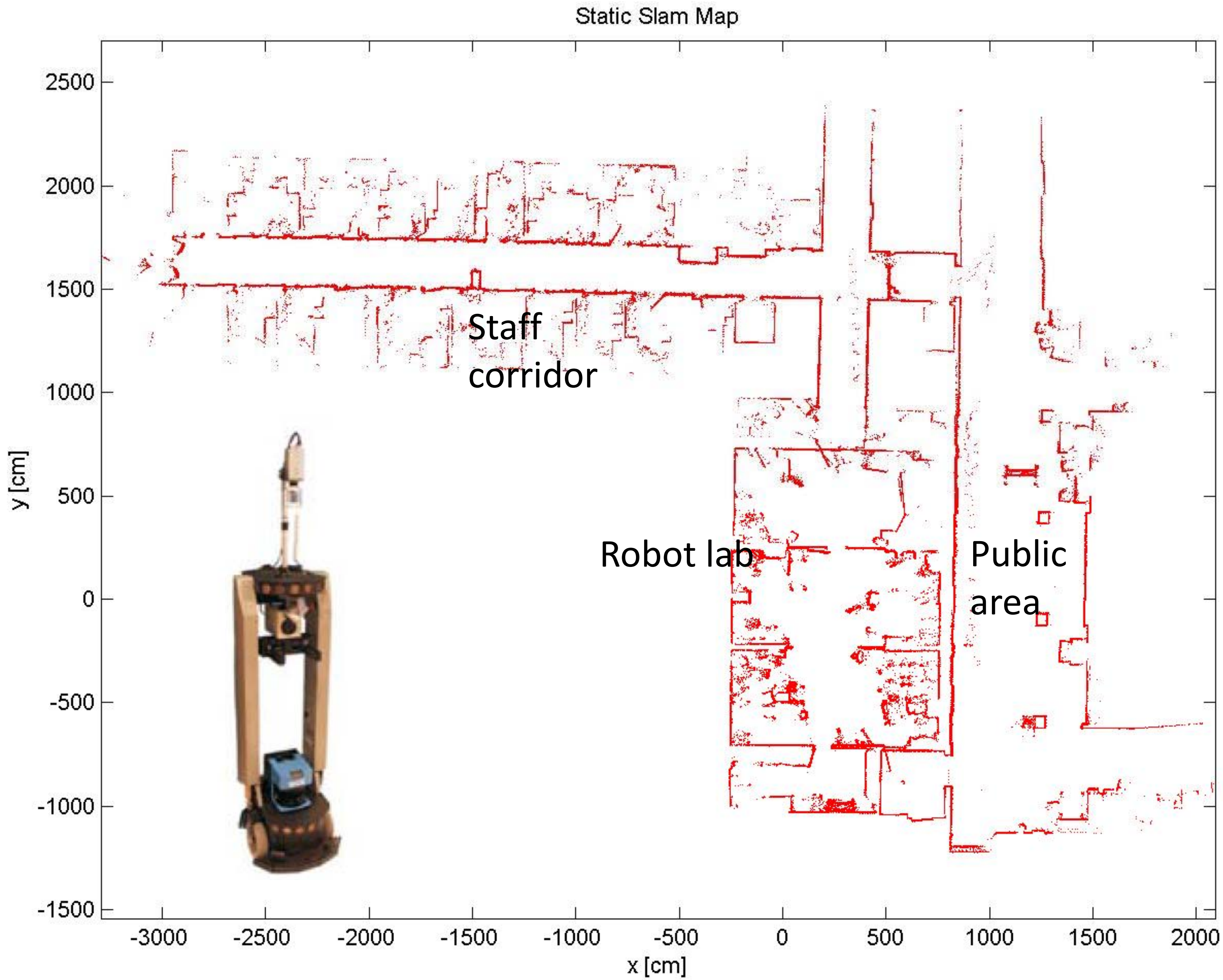
What are maps?

- Collection of elements or features at some scale of interest, and a representation of the spatial and semantic relationships among them



Types of Maps

- Metric Maps
  - Record the location of objects in an absolute coordinate system
- Topological Maps
  - Record the connections (links) between a set of places (nodes)
- Semantic Maps
  - Record semantic information (metadata), includes segmentation, place/object naming, function, etc.
- Hybrid Maps
  - Combine two or more of the map types above



Static Slam Map
Staff corridor
Robot lab
Public area
y [cm]
x [cm]
2500
2000
1500
1000
500
0
-500
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-1500
-3000
-2500
-2000
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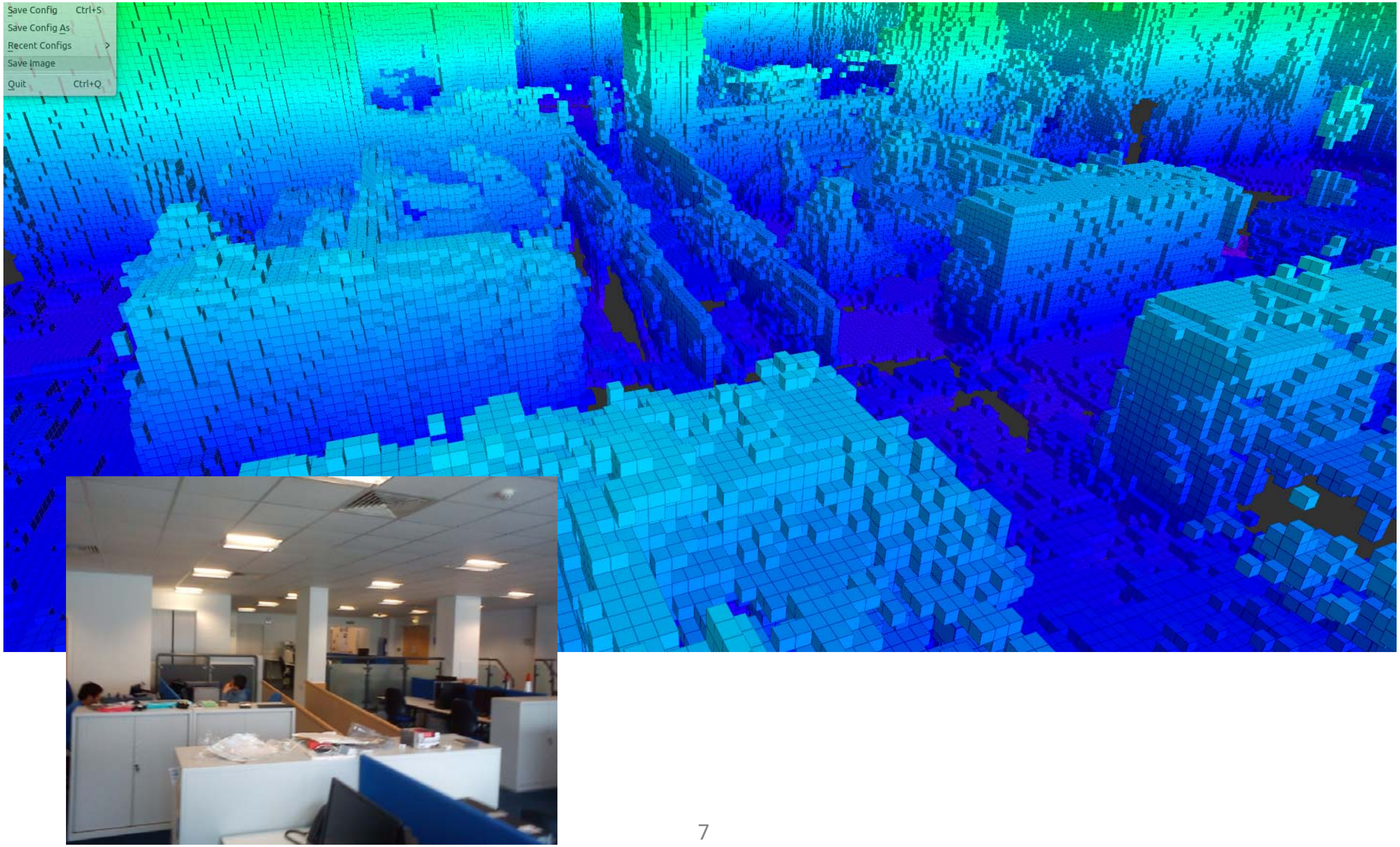
2000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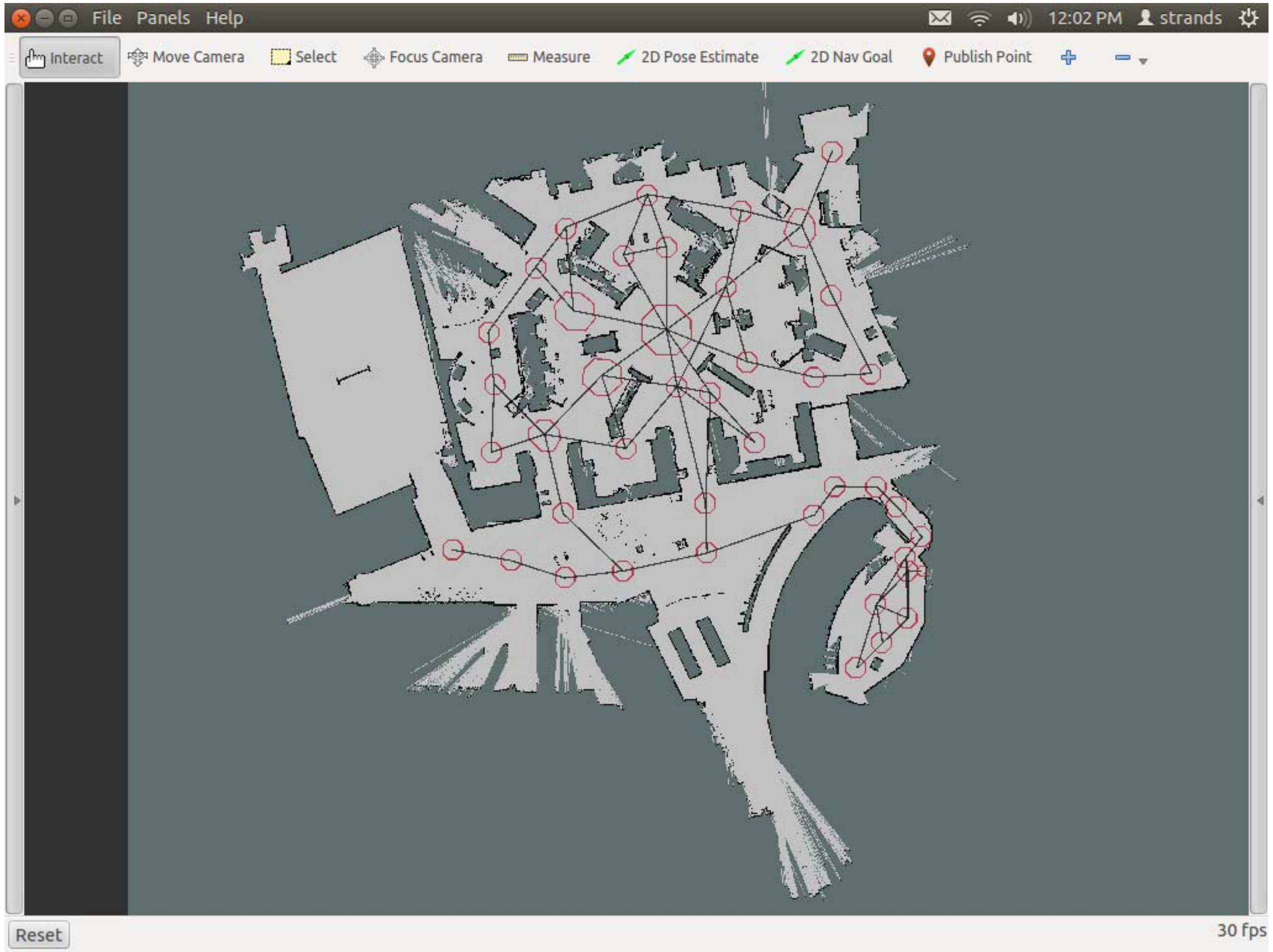
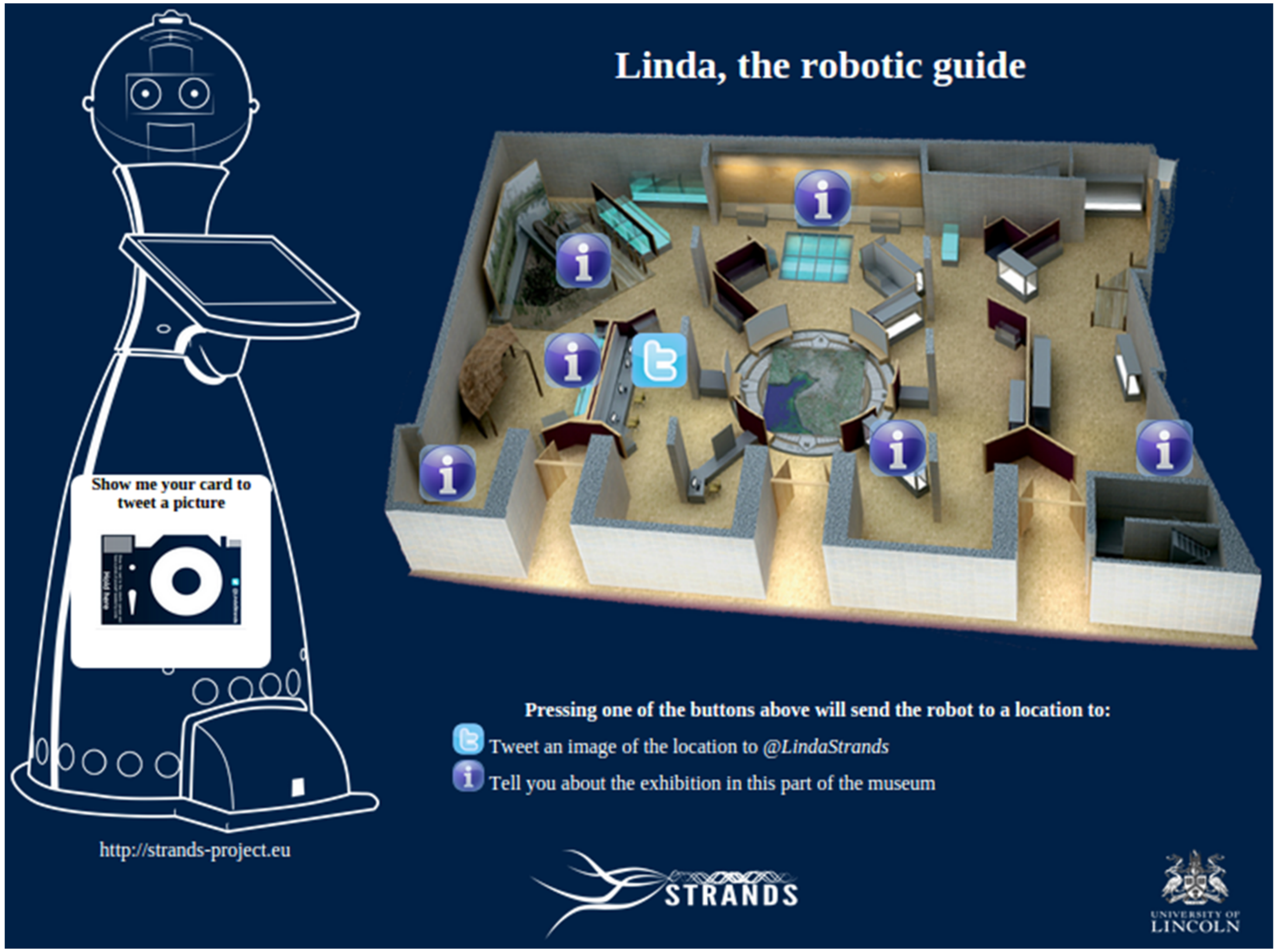
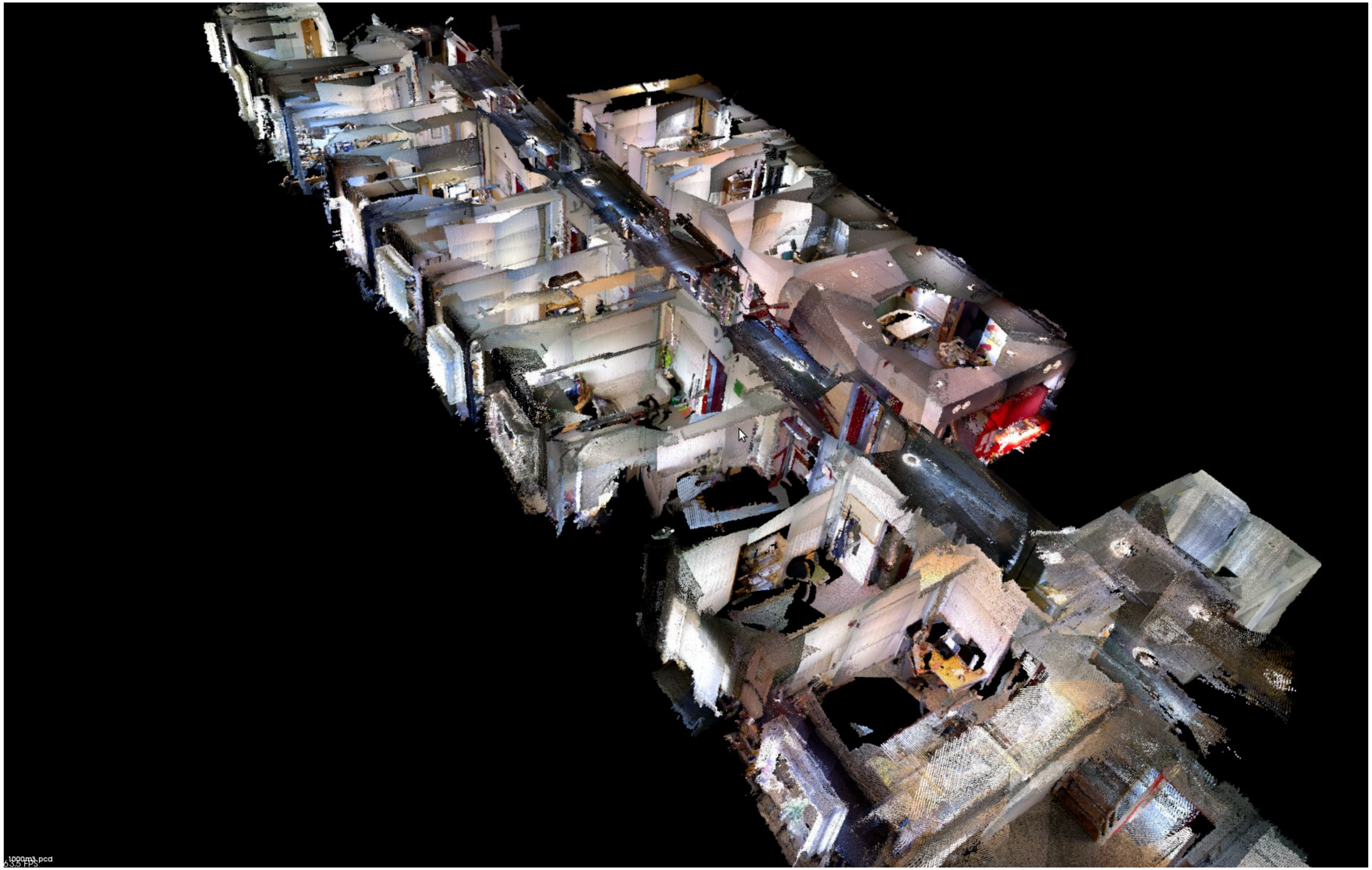
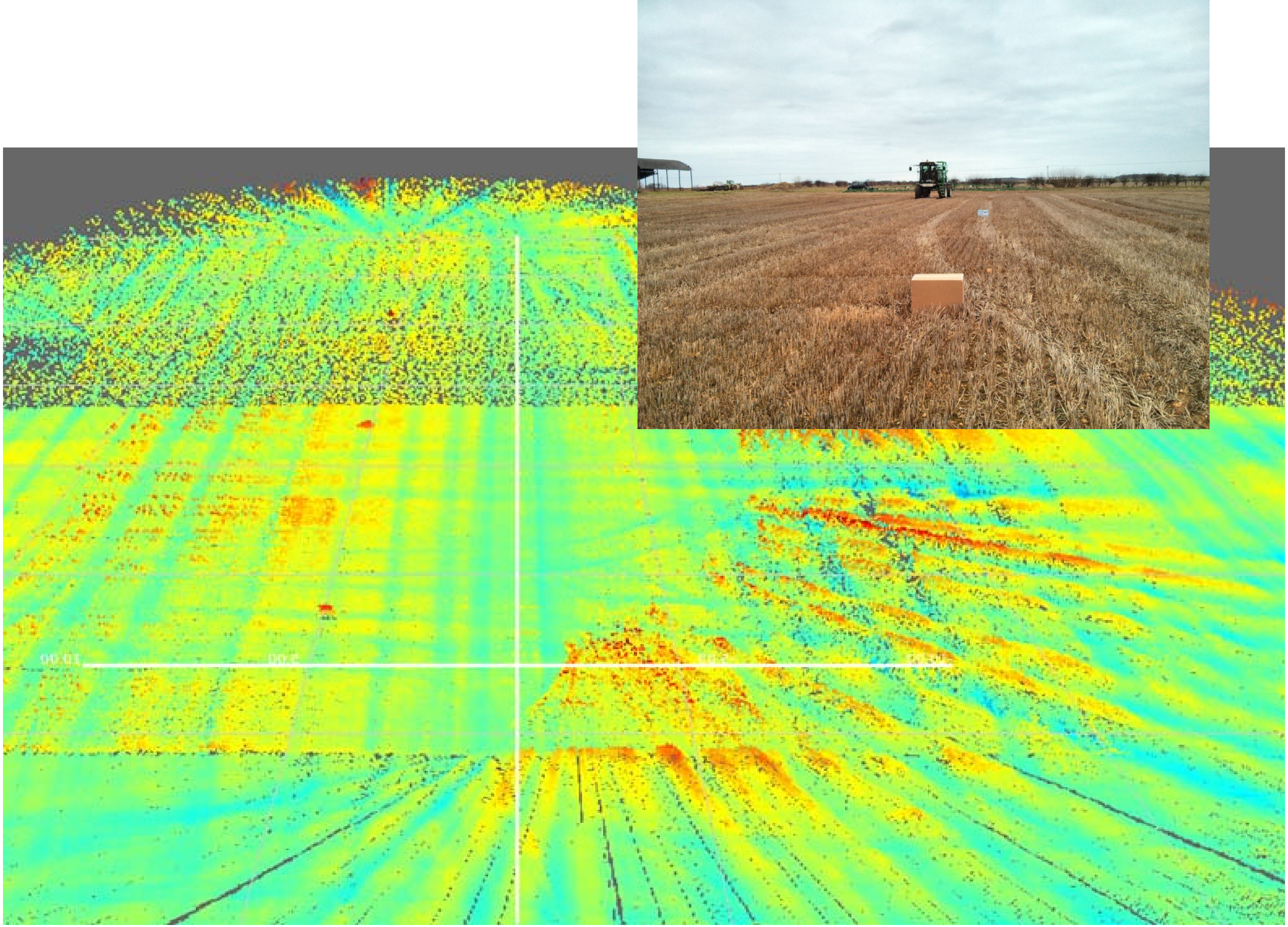
Linda's navigation map at the Collection Museum, Lincoln



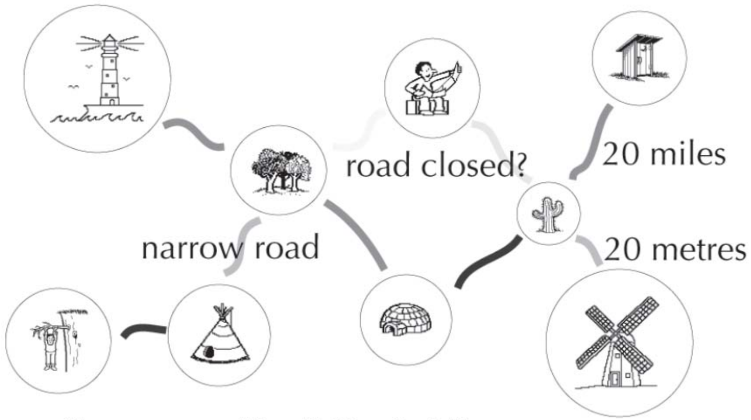
Linda’s touch-screen







Robot Maps



- Global map
  - topological
  - metric
- Local maps
  - e.g. defined at level of a "room", "field", etc.
  - background model + a set of objects that can move + human activities + ...
- Semantics, functional regions, dynamics, ...
- Knowledge representation for higher-level reasoning and planning

Long-Term Robotic Mapping

- Challenges for service robots:
  - Long-term operation
  - Large-scale dynamic environments
  - Live together with people

- Consequences for mapping and localisation:
  - Coping with dynamic and changing environments
  - Life-long learning and adaptation

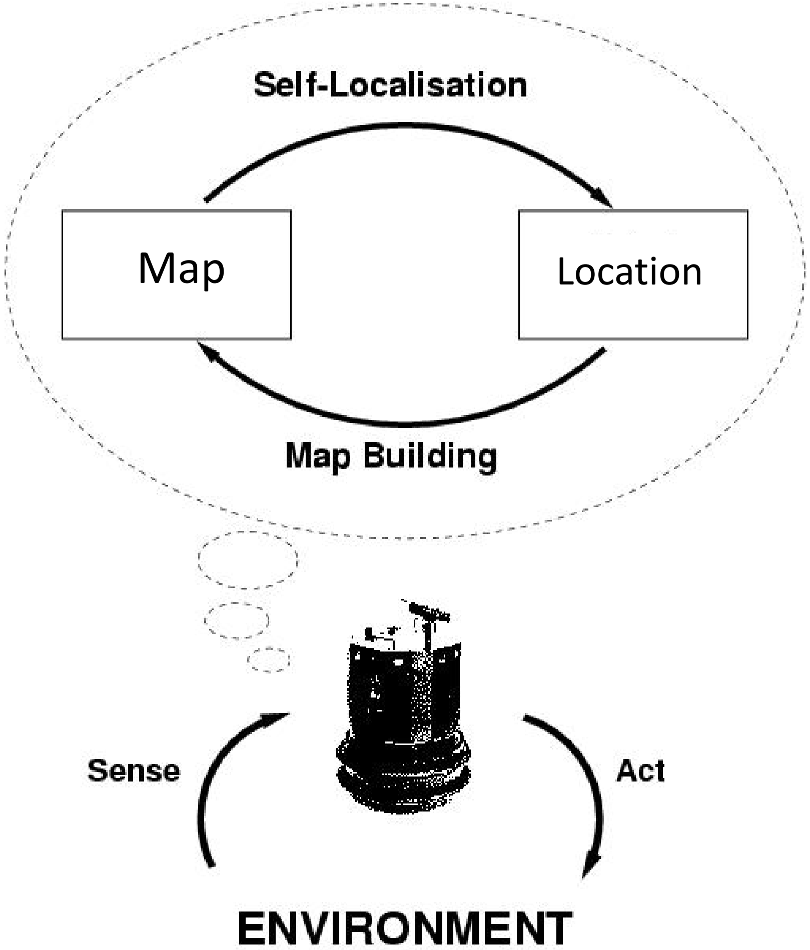
Dynamic Environments

MAPPING & LOCALISATION IN STATIC ENVIRONMENTS

Localization and Mapping

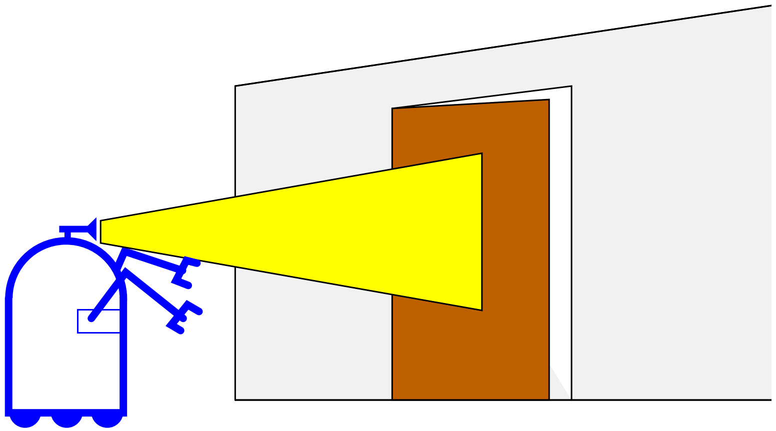
- SLAM = Simultaneous Localisation and Mapping

A "chicken and egg" problem!



Probabilistic Robotics

- Explicit representation of uncertainty using the calculus of probability theory



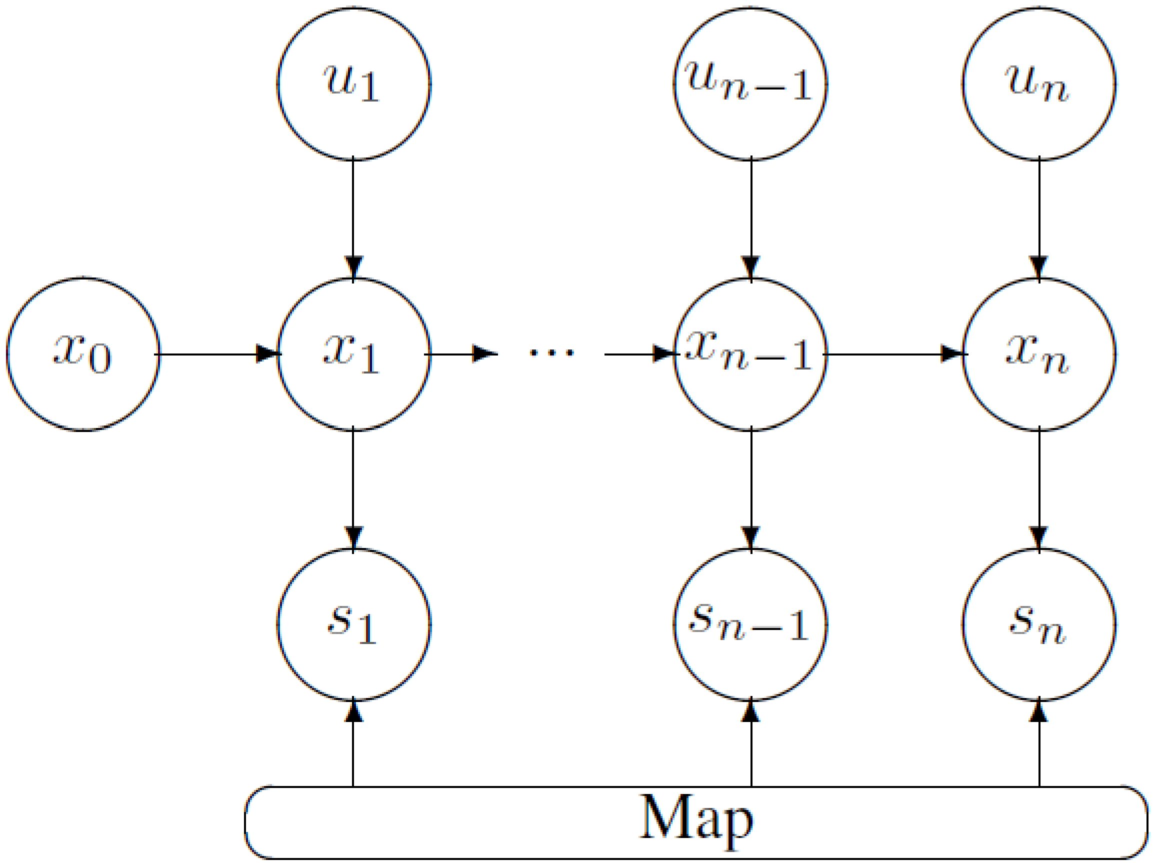
$$P(open \mid z) = \frac{P(z \mid open)P(open)}{P(z)}$$

S. Thrun, W. Burgard, and D. Fox, *Probabilistic Robotics*. MIT Press, 2005.

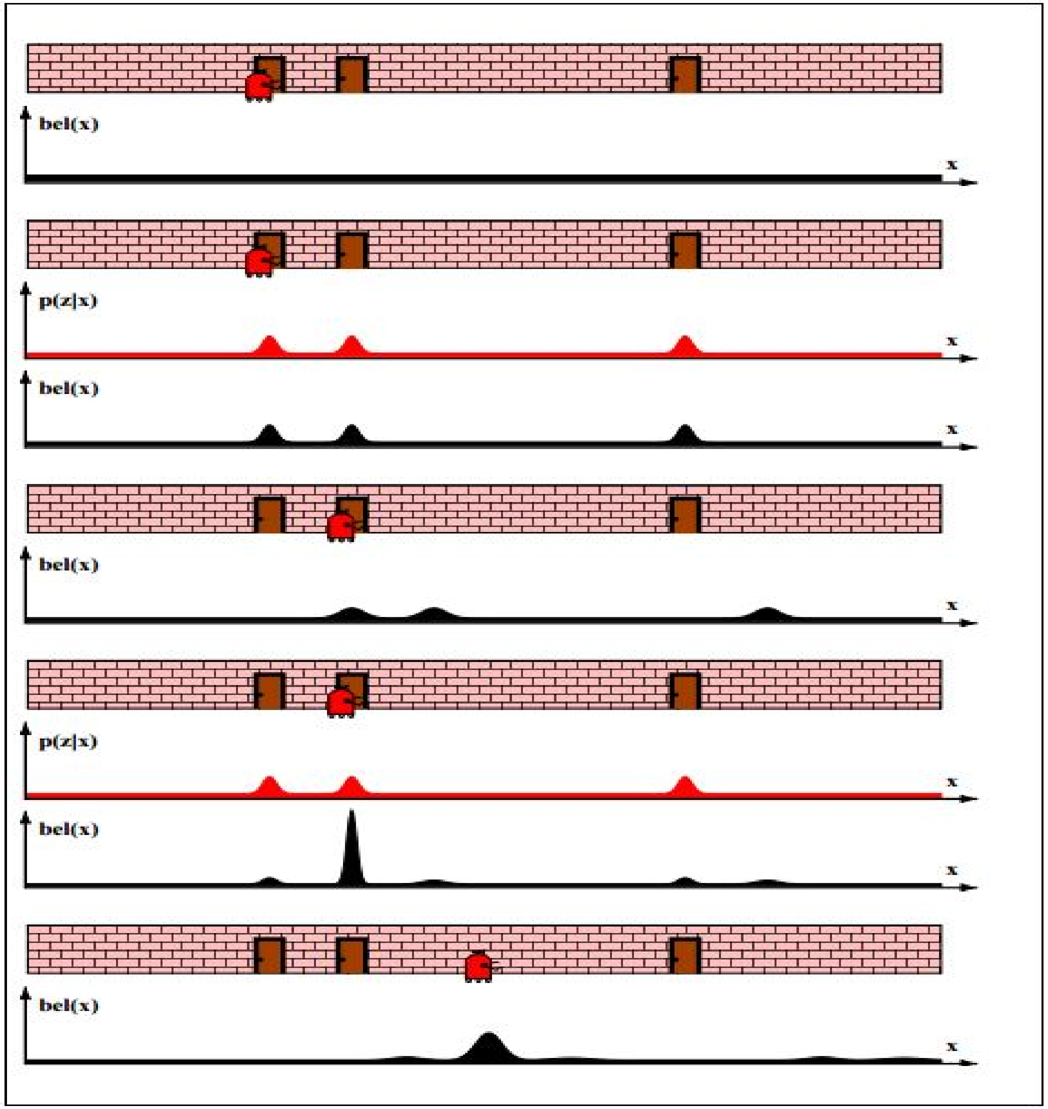
Markov Assumption

- Markov assumption: past and future data are independent if one knows the current state x_t
- "Static world"

Markov Localization

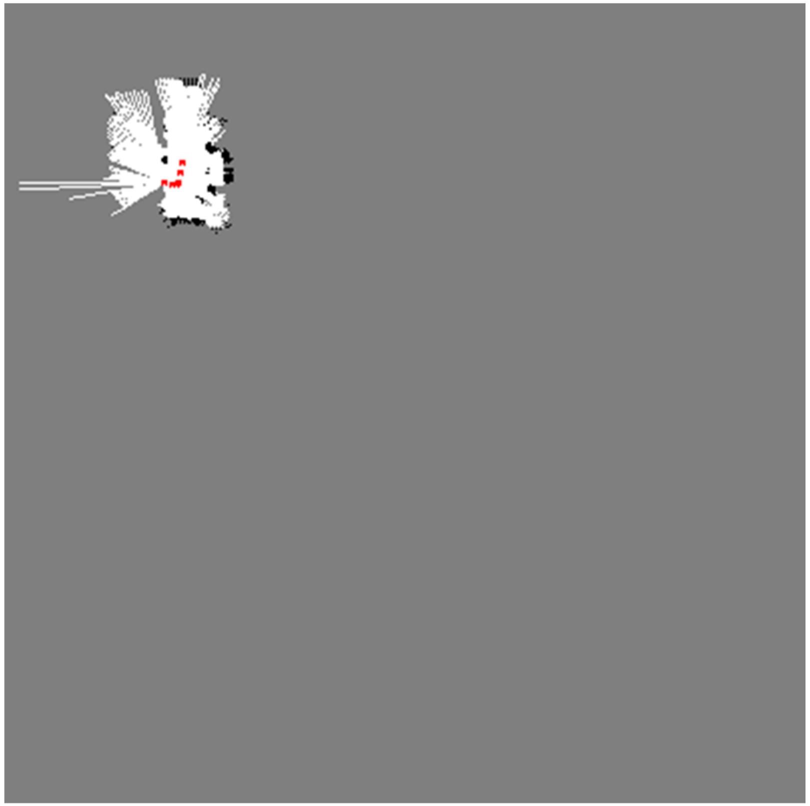


Markov Localization



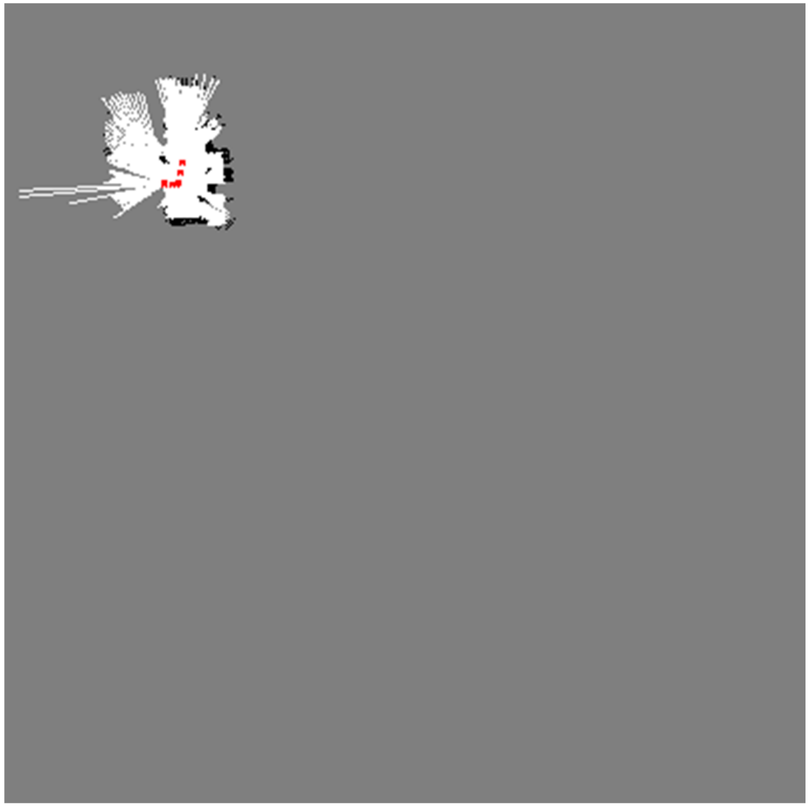
Localization and Mapping

- Example of automatic mapping (no SLAM)



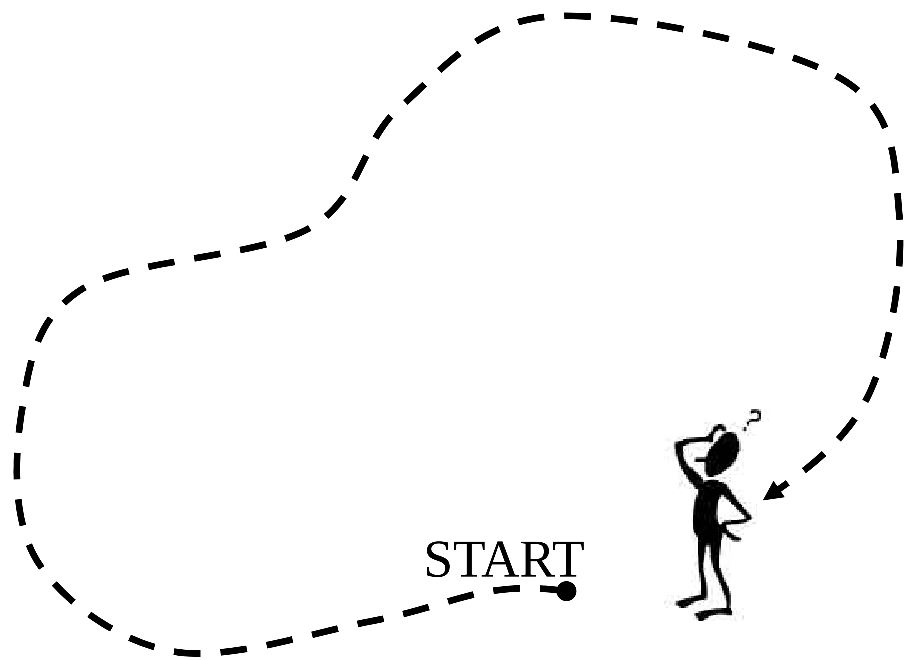
Localization and Mapping

- Example of automatic mapping (with SLAM)



Data Association

- Which parts of the current observation correspond to which parts of the map?



  - e.g. “loop closing” problem in SLAM

MAPPING & LOCALISATION IN CHANGING ENVIRONMENTS – APPROACH 1: DYNAMIC MAP

Varying Environments

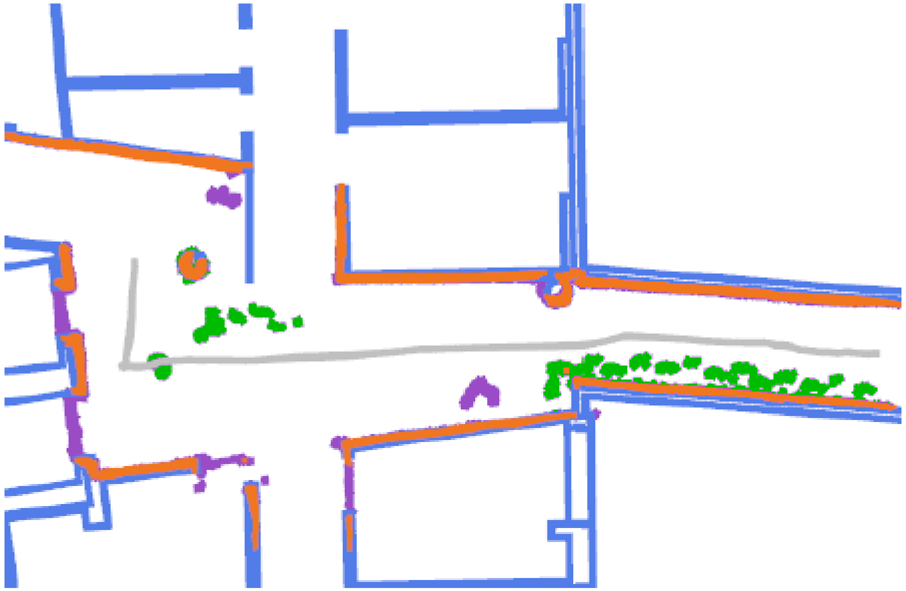


Figure 2.2: Non-Markov nature of robot observations, shown by plotting laser rangefinder observations over multiple time steps, and registered by non-Markov localization to a static map (blue lines). The observations include observations that can be explained by the map (orange points), observations that can be explained by movable, but currently static objects like the potted plant and doors(purple points), and moving objects like humans(green points). The robot trajectory is plotted in gray.

J. Biswas, *Hybrid Markov / Non-Markov Localization for Long-Term Autonomy of Mobile Robots in Varying Indoor Environments*. PhD Thesis Proposal, Carnegie Mellon University, 2013.

Varying + Changing Environments

- Moving people or robots
- Movable objects (tables, chairs)
- Temporary objects (packages)
- Gradual changes (plants grow)
- Abrupt change (a new wall is built)

The Stability-Plasticity Dilemma

- Life-long learning requires:
  - Adaptation to new patterns, and
  - Preservation of old patterns

Stability ⟷ *Plasticity*

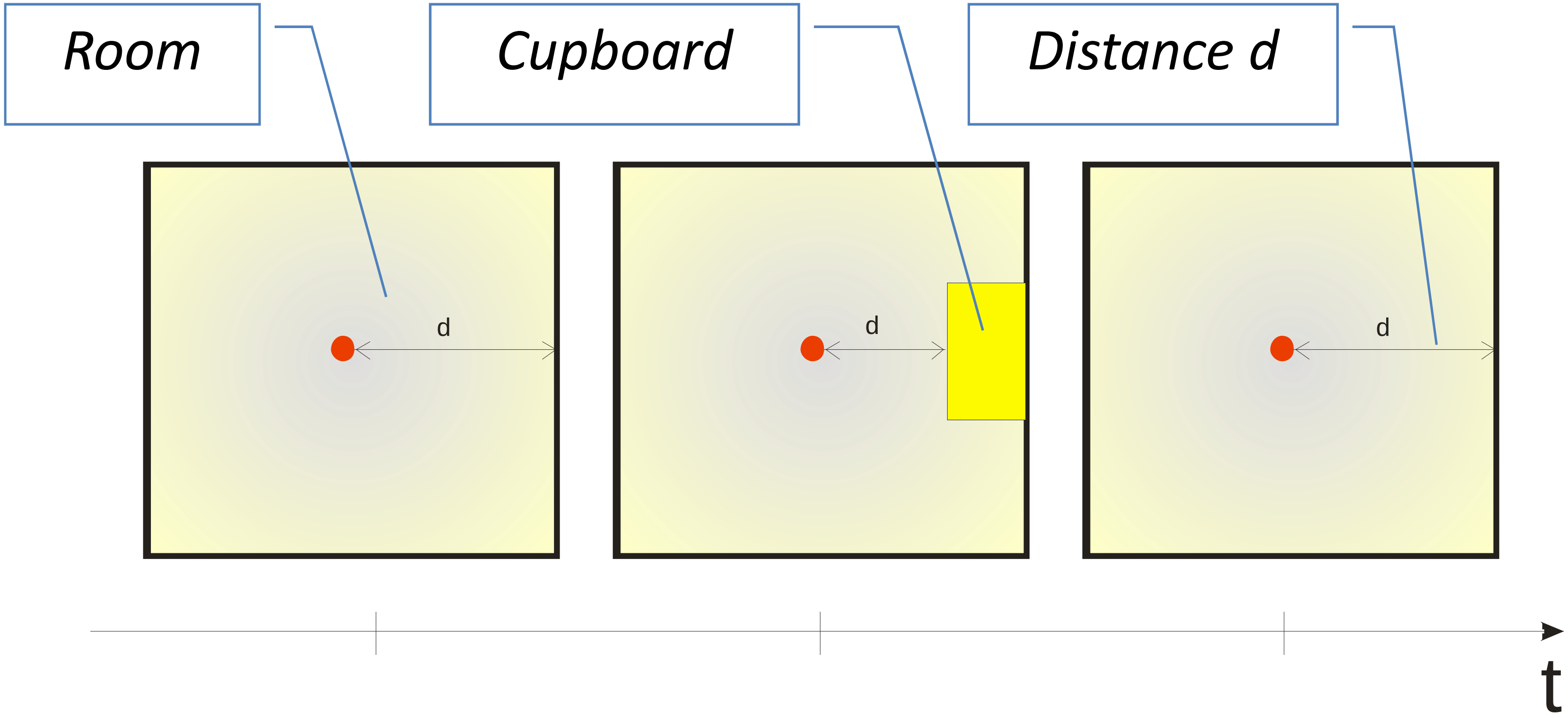
Robot motion

Transient changes

Lasting changes

Biber, Peter and Duckett, Tom (2009) *Experimental analysis of sample-based maps for long-term SLAM.* International Journal of Robotics Research, 28 (1).

Toy Example



Simple map:
Only entry is distance *d*

Approaches to dynamic mapping

- Mean distance (Running average):

$$\hat{d} = \frac{1}{n}\sum_{i=1}^{n} d_i \qquad \hat{d}_t = \frac{1}{n}(d_t + (n-1)\hat{d}_{t-1})$$

Not well suited.

The time that the map needs for adapting to a change should not be dependent on how much time has been passed in absolute terms.

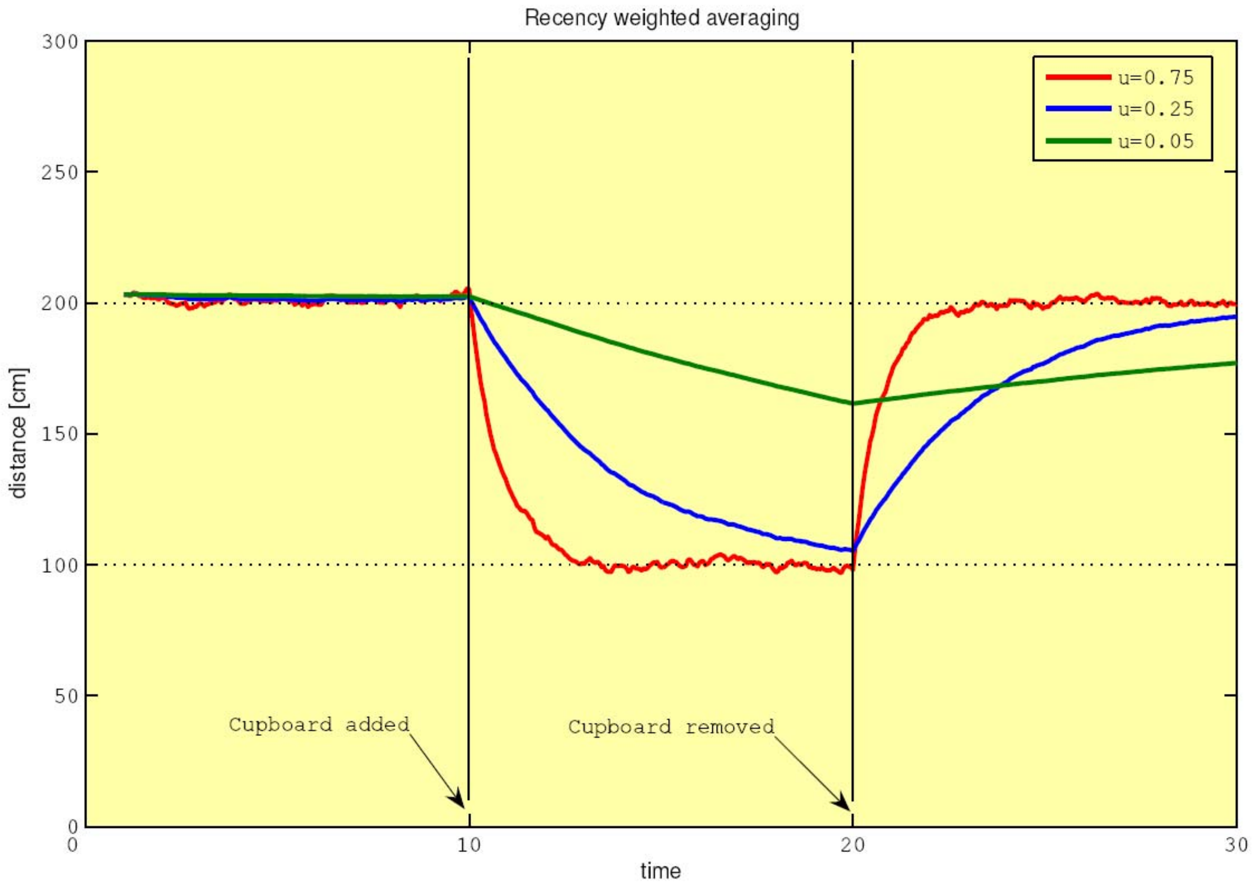
Approaches to dynamic mapping

- Recency weighted averaging
- Measurement has an age *t*

$$\hat{d} = \frac{1}{n}\sum_{i=1}^{n} e^{-\lambda t_i} d_i \qquad \hat{d}_t = \alpha d_t + (1-\alpha)\hat{d}_{t-1}$$

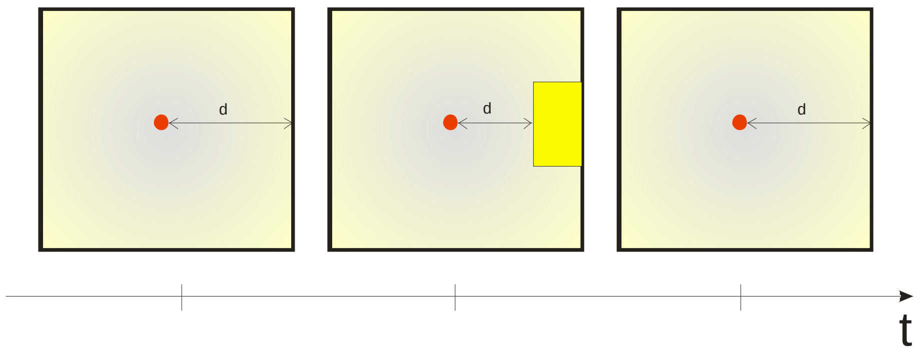
Observation: The law that governs the update of a dynamic map is inherently dependent on a time scale parameter.

Simulation of the toy example



Approaches to dynamic mapping

- Problems of recency weighted averaging:
  - Cannot handle non-continuous changes
  - Not robust against outliers
  - Cannot maintain multiple hypotheses



- Dynamic map should give distance to wall or to cupboard but nothing inbetween

The problem of outliers

- Notorious problem in Least-Squares formulations (classical statistics)

- **Outlier declaration is not possible directly after the measurement!**
- Unexpected sensor reading:
  - Might be an outlier
  - Might be a change
- Can only be said after more sensor readings, and depends also on the timescale.
- ***Must maintain both hypotheses***

Our solution (part 1)

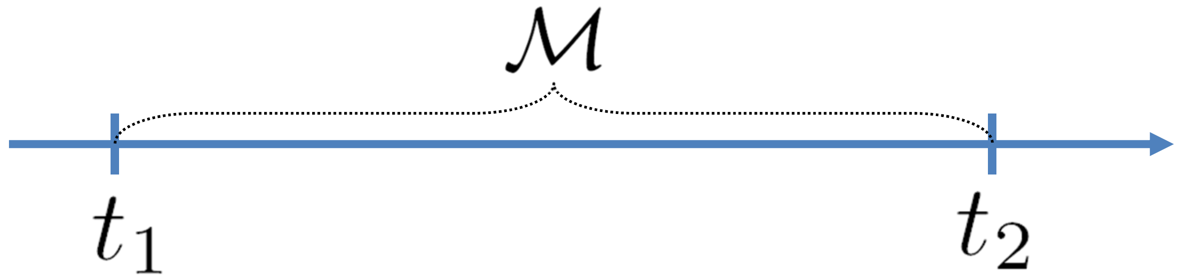
- Representation of measurements by a set of samples
- Interpretation of samples by robust statistics (median and MAD)
- Update dynamic map by replacing samples

✓ Can maintain multiple hypotheses
✓ Robust against outliers
✓ Estimates are only values that have actually been measured

Update of a sample set

Samples $\mathcal{S}(t_1)$ $\mathcal{S}(t_2)$

Measurements



Number of samples *n* = constant

Replacement determined by *update ratio 0 < u < 1*:

1. Remove *n*u* randomly chosen samples from $\mathcal{S}(t_1)$
2. Add *n*u* randomly chosen samples from $\mathcal{M}$

Semantics of a sample set

- Probability that a sample is *t* time steps old:

$$
\begin{aligned}
& p(t) \\
& = u\,(1-u)^t \\
& = u\, e^{\ln(1-u)\,t}
\end{aligned}
$$

- Age of samples is distributed like the weights in recency weighted averaging:

$$\lambda = -\ln(1-u)$$

Semantics of a sample set

$$\text{Mean life time}: \tau = \lambda^{-1}$$

$$\text{Half-life}: t_{1/2} = \frac{\ln 2}{\lambda}$$

Probabilistic interpretation

- Estimate parameters of Gaussian using robust statistics (*Median* and *MAD)*

$$\begin{aligned} \hat{\rho} &= \operatorname{median}(\mathcal{S}(t)) \\ \hat{\sigma} &= 1.48 \ \operatorname{median}(|x - \hat{\rho}|, x \in \mathcal{S}(t)) \end{aligned}$$

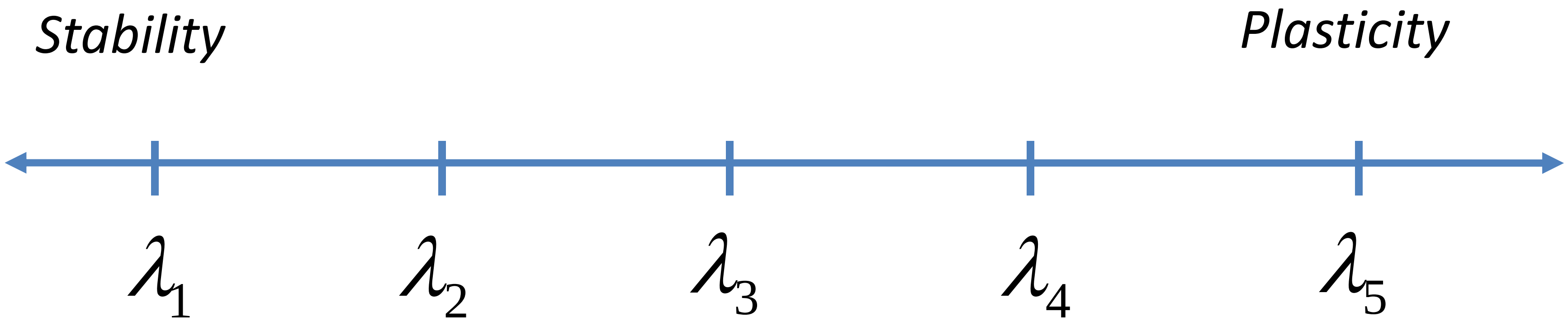
- Outlier ratio: sample considered inlier, if

$$|x - \hat{\rho}| < 3\hat{\sigma}$$

- otherwise outlier (99.7% confidence level)

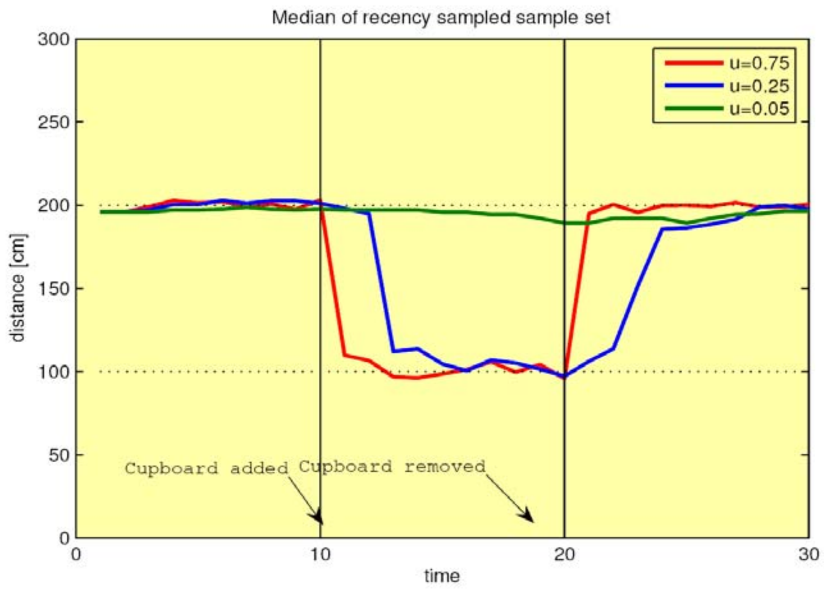
Our solution (part 2)

- There is no single “correct” timescale (stability-plasticity dilemma)
- Maintain map simultaneously at multiple timescales (5 in our experiments)

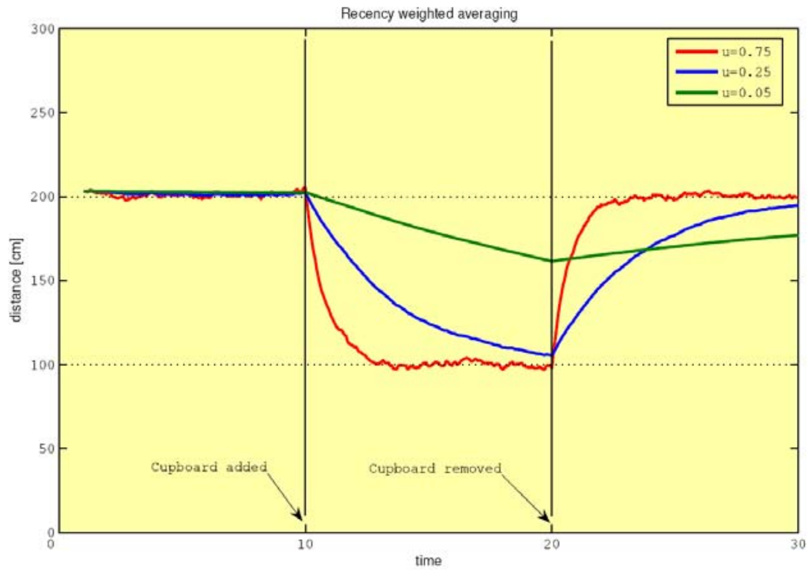


Simulation of the toy example

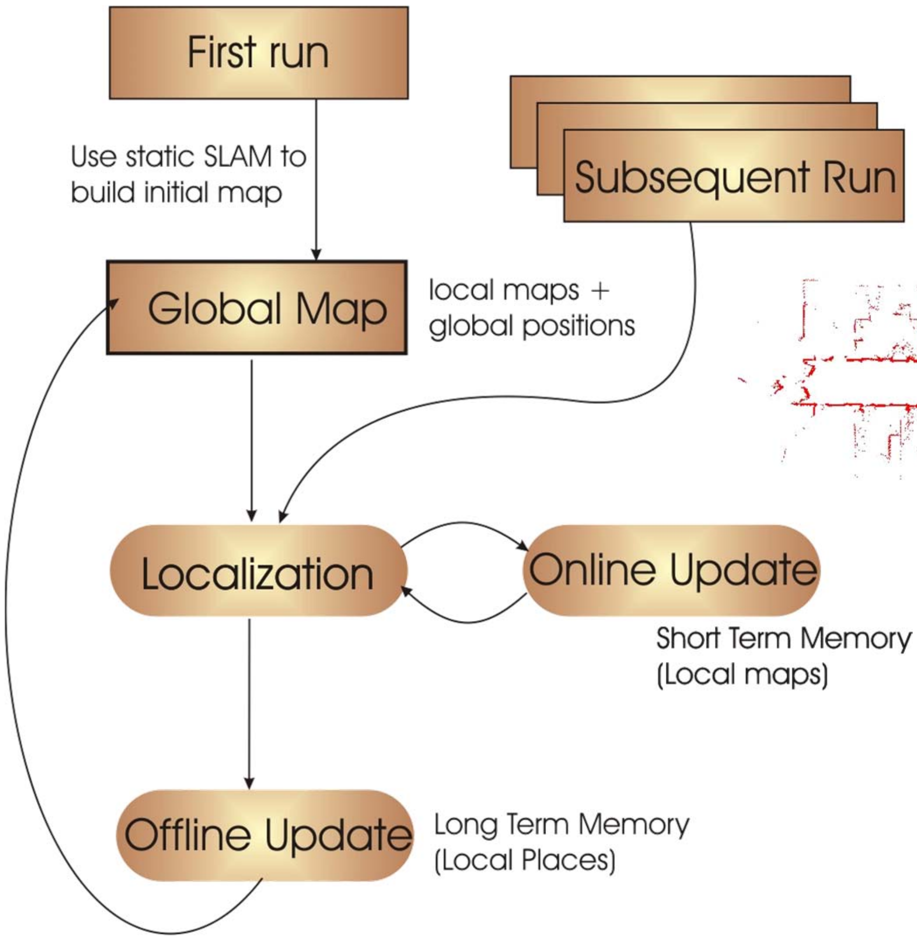
Sample-based map



Recency weighted average

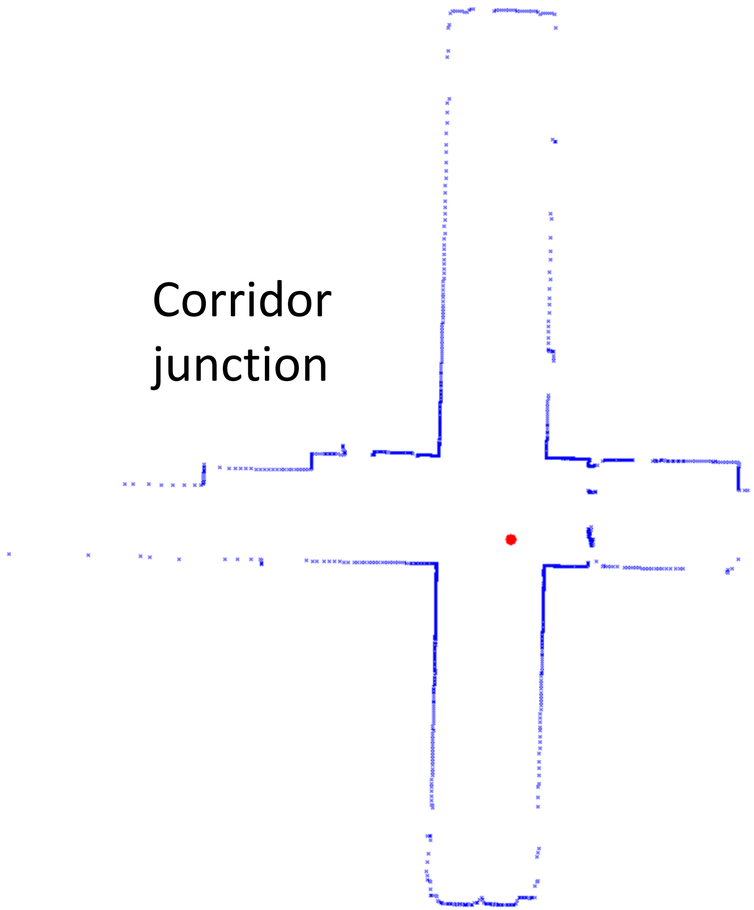


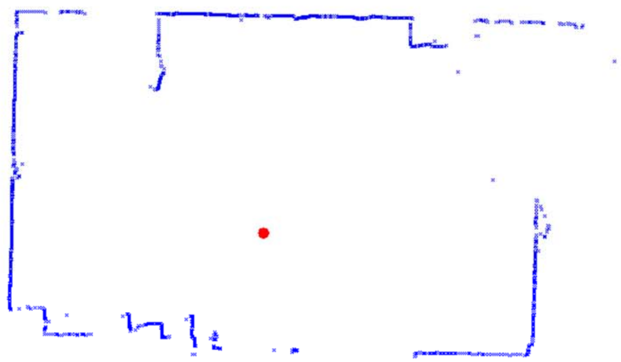
A complete system for lifelong mapping and localization



Initial static SLAM map

Local Maps





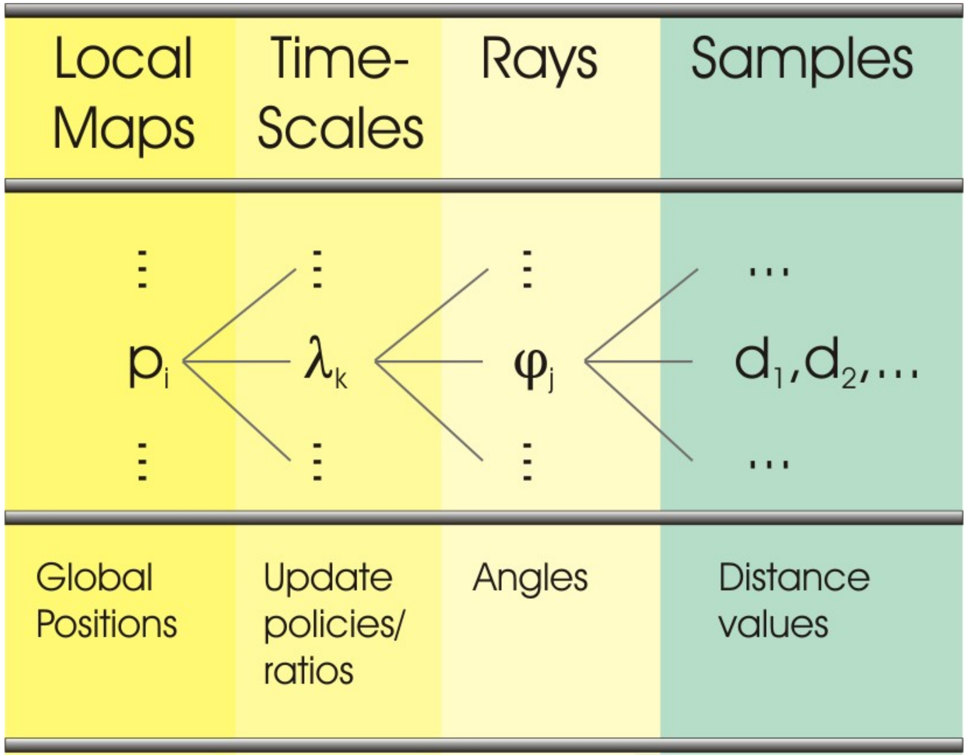
- Observations (laser scans) are projected into the same local coordinate system before updates

Local Maps

- Initial set of 76 local maps
- Selected from first run using heuristics
- More added online as needed

Local Maps

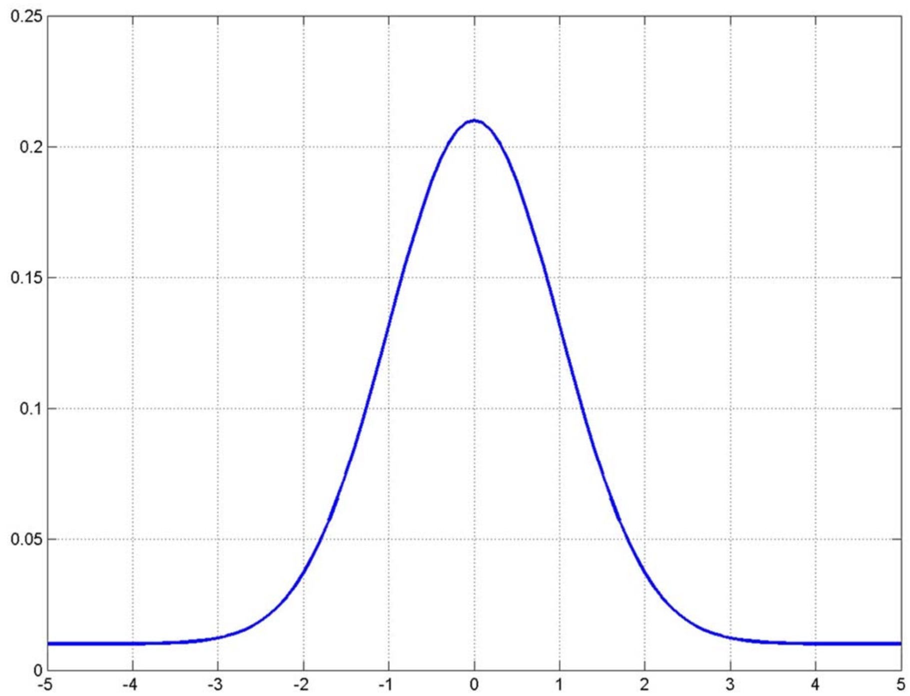
- 5 timescales
- Online update (STM)
- Offline update (LTM)



Upd. ratio	Upd. Interval	Time-scale ($t_{1/2}$)	n_{Rays}	n_{Samples}
$u = 0.2$	always	$t_{1/2} \approx 3.1$	360 (1 ray/°)	5
$u = 0.8$	after each run	$t_{1/2} \approx 0.43$ runs	360 (1 ray/°)	10
$u = 0.8$	daily	$t_{1/2} \approx 0.43$ days	720 (2 rays/°)	50
$u = 0.2$	daily	$t_{1/2} \approx 3.1$ days	1440 (4 rays/°)	100
$u = 0.05$	daily	$t_{1/2} \approx 13.5$ days	1440 (4 rays/°)	100

Perceptual model for local map selection

- Probability of a measuring a range value given
  - a local map
  - a time-scale
  - a time t



- Mixture model: Gaussian + Outlier

$$p(d) = (1 - p_{\text{outlier}})p_{\text{normal}}(d) + p_{\text{outlier}} * p_{\text{uniform}}(d)$$

Self-localization (position tracking)

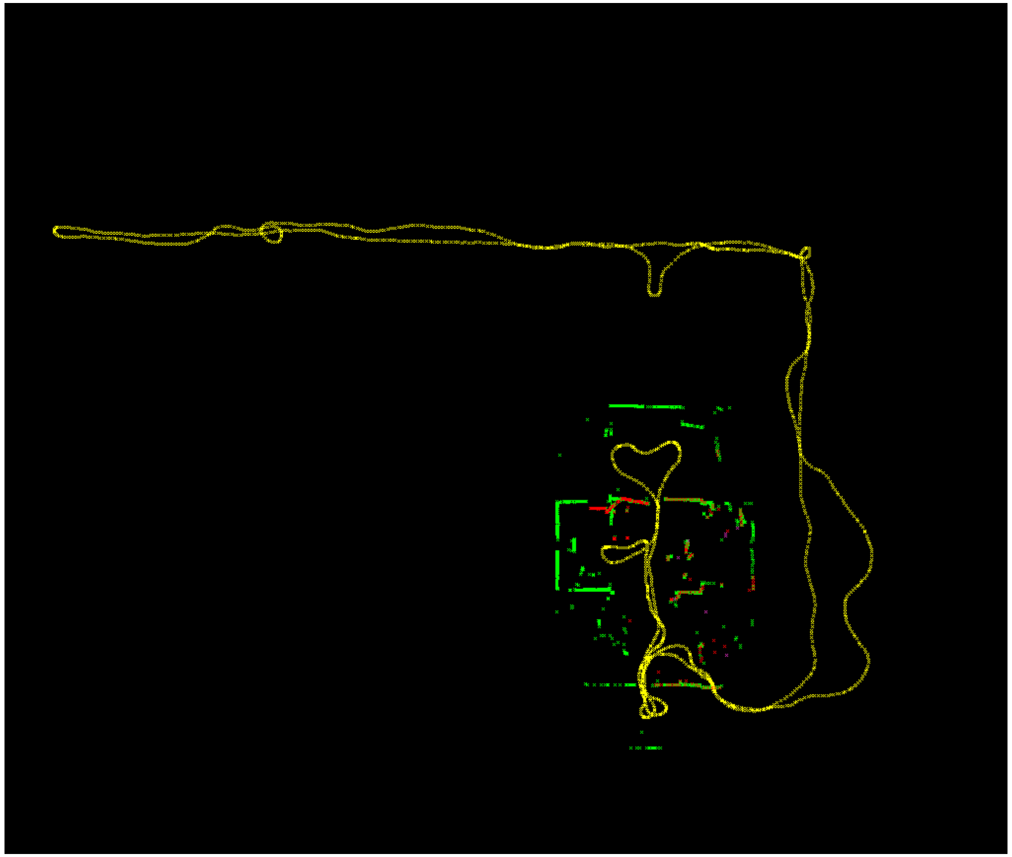
- Current Map is defined according to:
  - Local maps
  - Current position estimate
  - Sensor input
- and is built on-the-fly when needed

- Selection of the time-scale in a local map is *data-driven* (choose the time-scale that best fits the data)

Self-localization (position tracking)

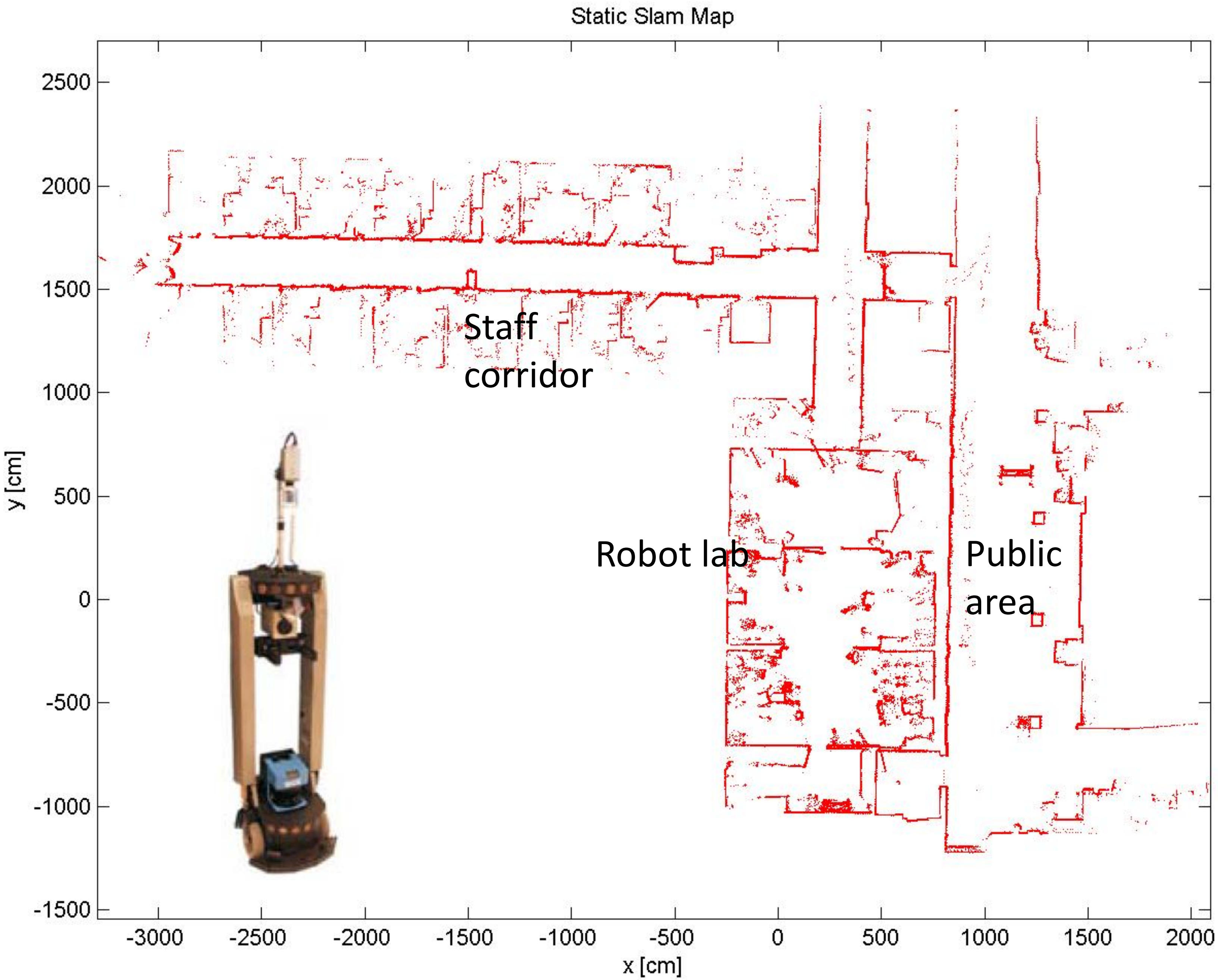
- Current Map: Green
- Current Scan: Red
- Trajectory: Yellow

- Scan Matching using odometry as prior: *Next Scan* vs. *Current Map*



Experiments

- 5 weeks (23 days)
- 75 runs (~3 per day)
- ~100 000 scans
- ~9.6 km
- Robot steered manually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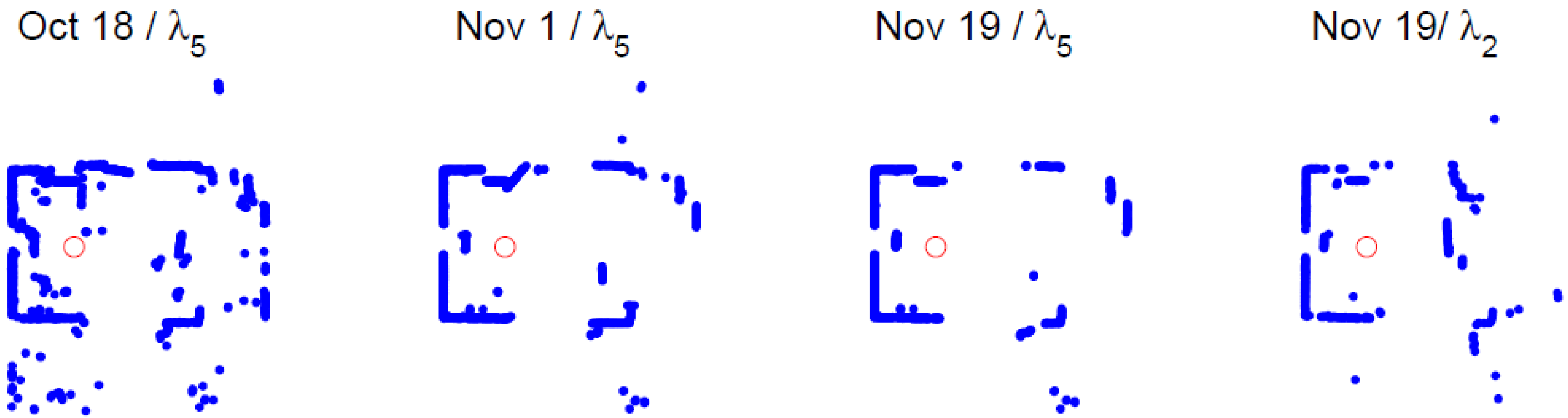
2000

Experiments

- Example of a dynamic environment (AASS robotics lab, Örebro)

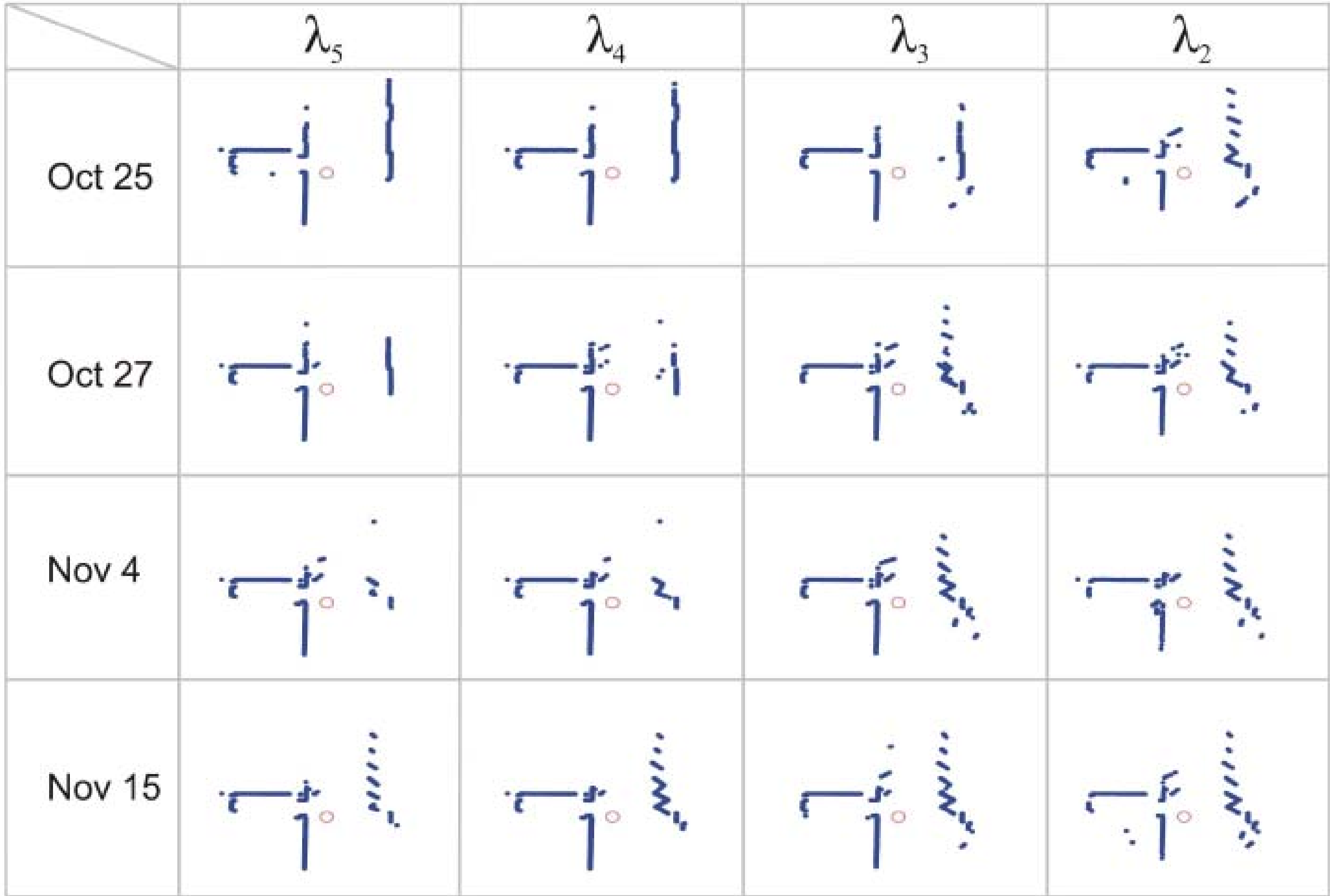
Experiments

Results



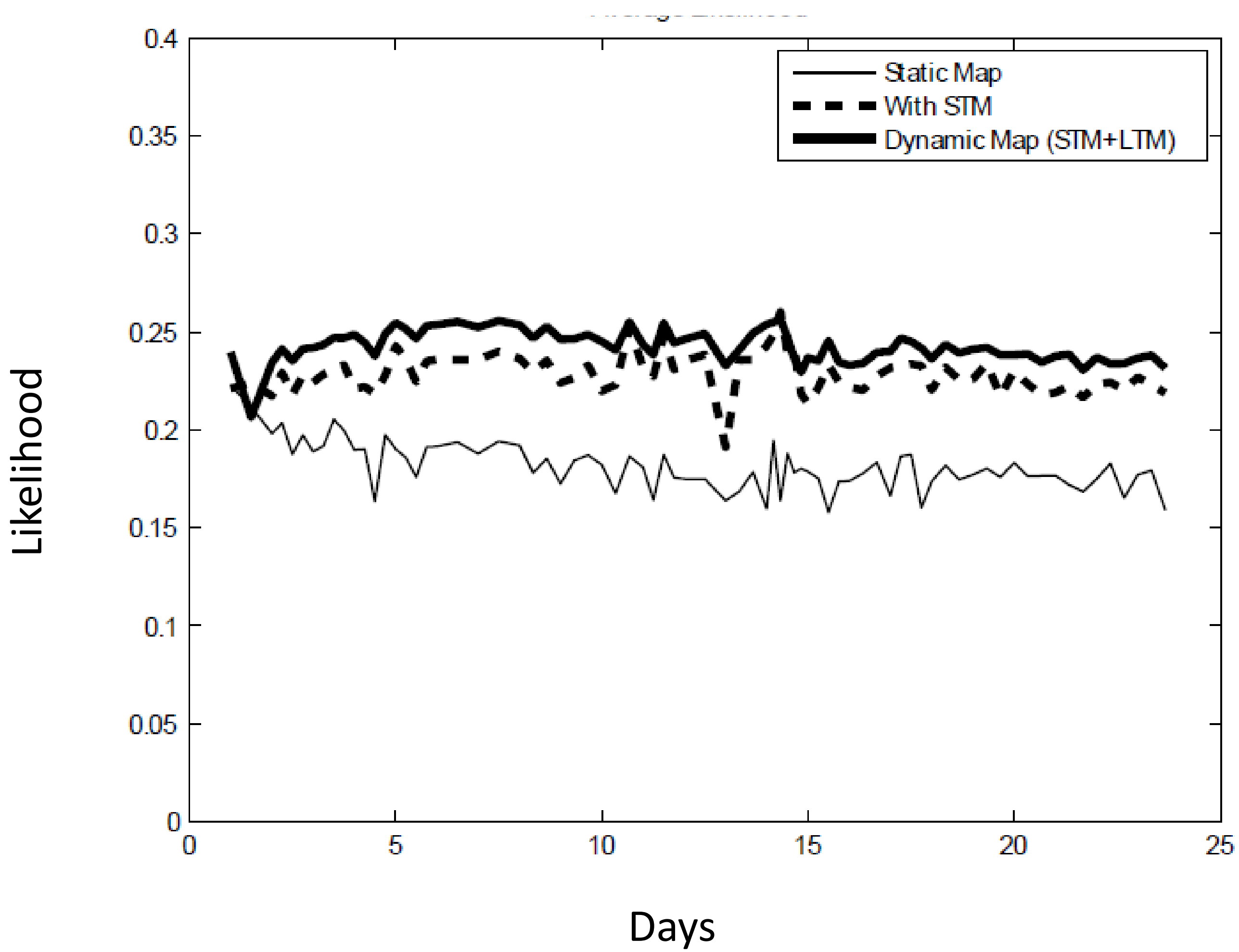
- Accuracy of maps increases with time
- Static parts like walls emerge, while moving objects disappear from long-term maps

Results



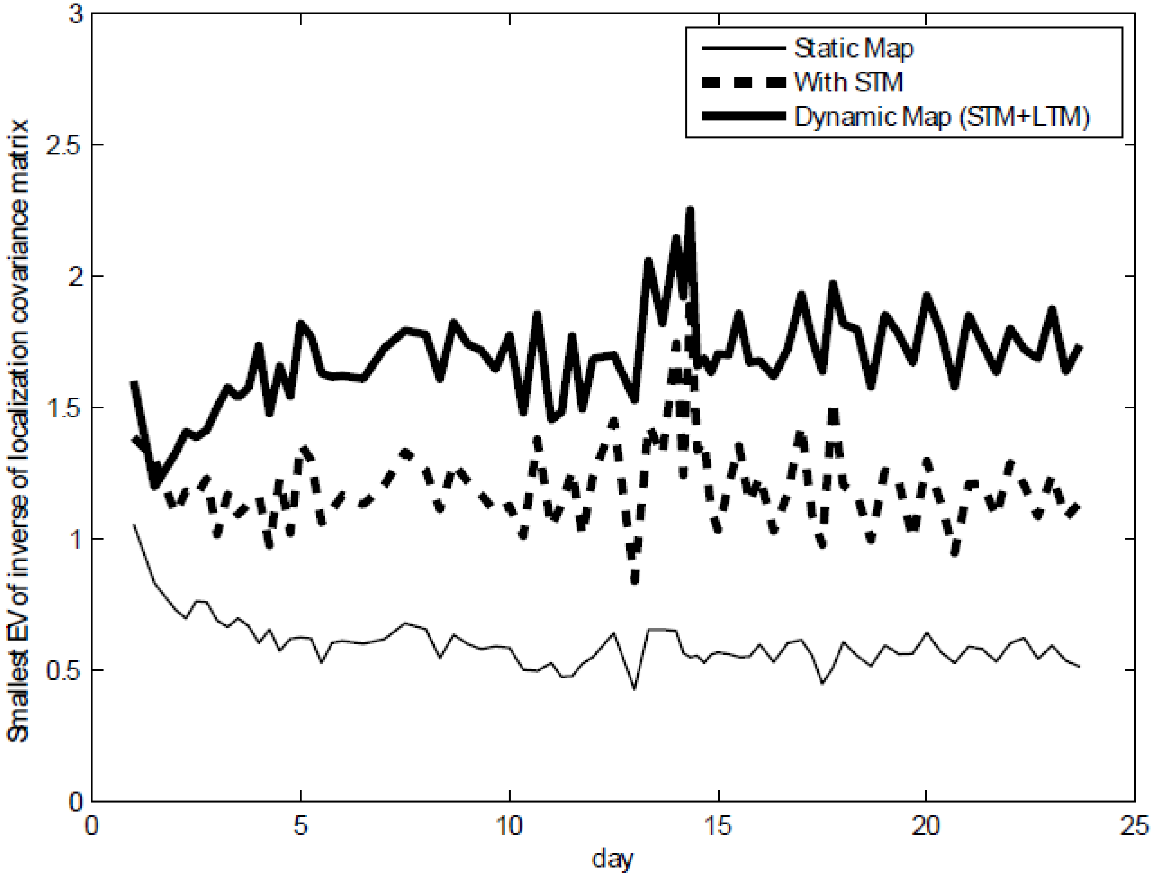
Results

- Average likelihood of a range measurement

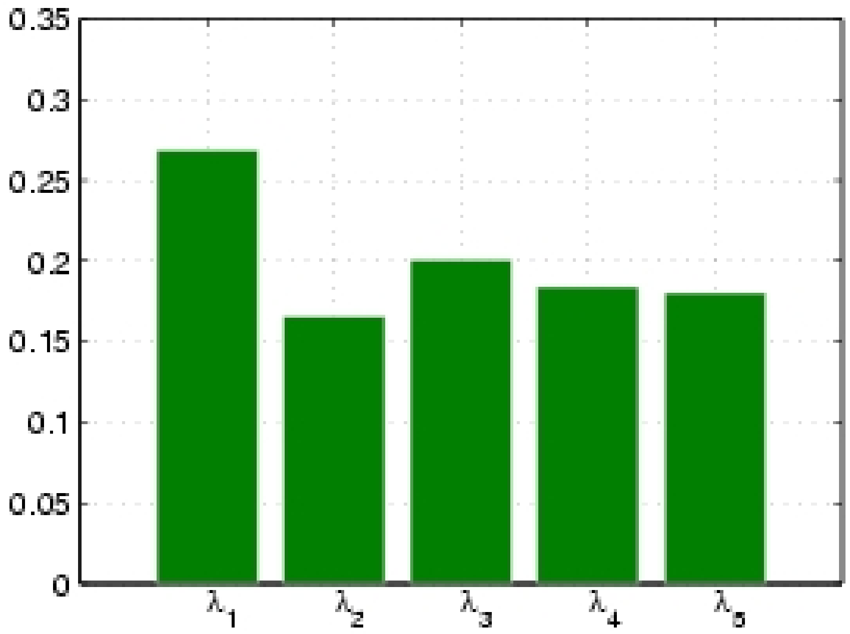


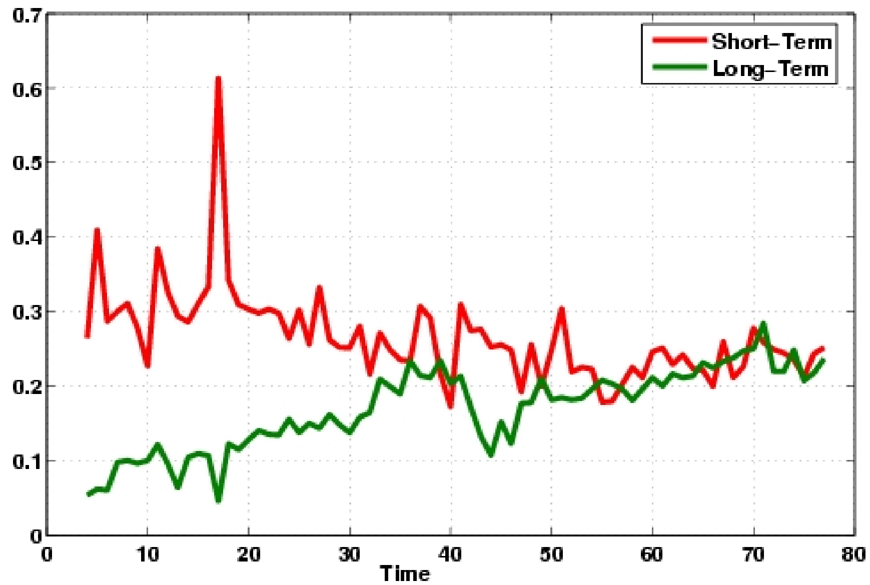
Results

- Certainty of the localization estimate



Relative frequency of submap usage





- All long-term maps are used with similar frequency, short-term map is used more often
- But with time, longest-term map is used more, short-term map is used less

Conclusions

- Static SLAM:
  - One-shot learning or averaging without forgetting
  - “First impression lasts forever“
- Dynamic Mapping:
  - Robot never stops learning (and forgetting!)
  - Beginning of time has no special status

Conclusions

- Outlier vs. change?
  - Need to store both hypothesis
  - Our solution: dynamic sample sets interpreted using robust statistics
- Stability-plasticity dilemma
  - Our solution: learning across multiple timescales
- Segmentation-free approach
  - No need to classify “static” vs “dynamic” parts

Conclusions

- "Exploitation vs. Exploration"
  - LTM: robustly use what you know already
  - STM: switch to "SLAM" if the world has changed
- Take care with datasets and simulations!
  - Offline experiments have a start and end time
  - vs. Lifelong adaptation

Limitations

- Memory requirements
  - Over 300,000 samples per local map
  - 60MB in total
- How to determine the timescale parameters?
- Long-term topological changes not considered