Mapping in Dynamic Environments

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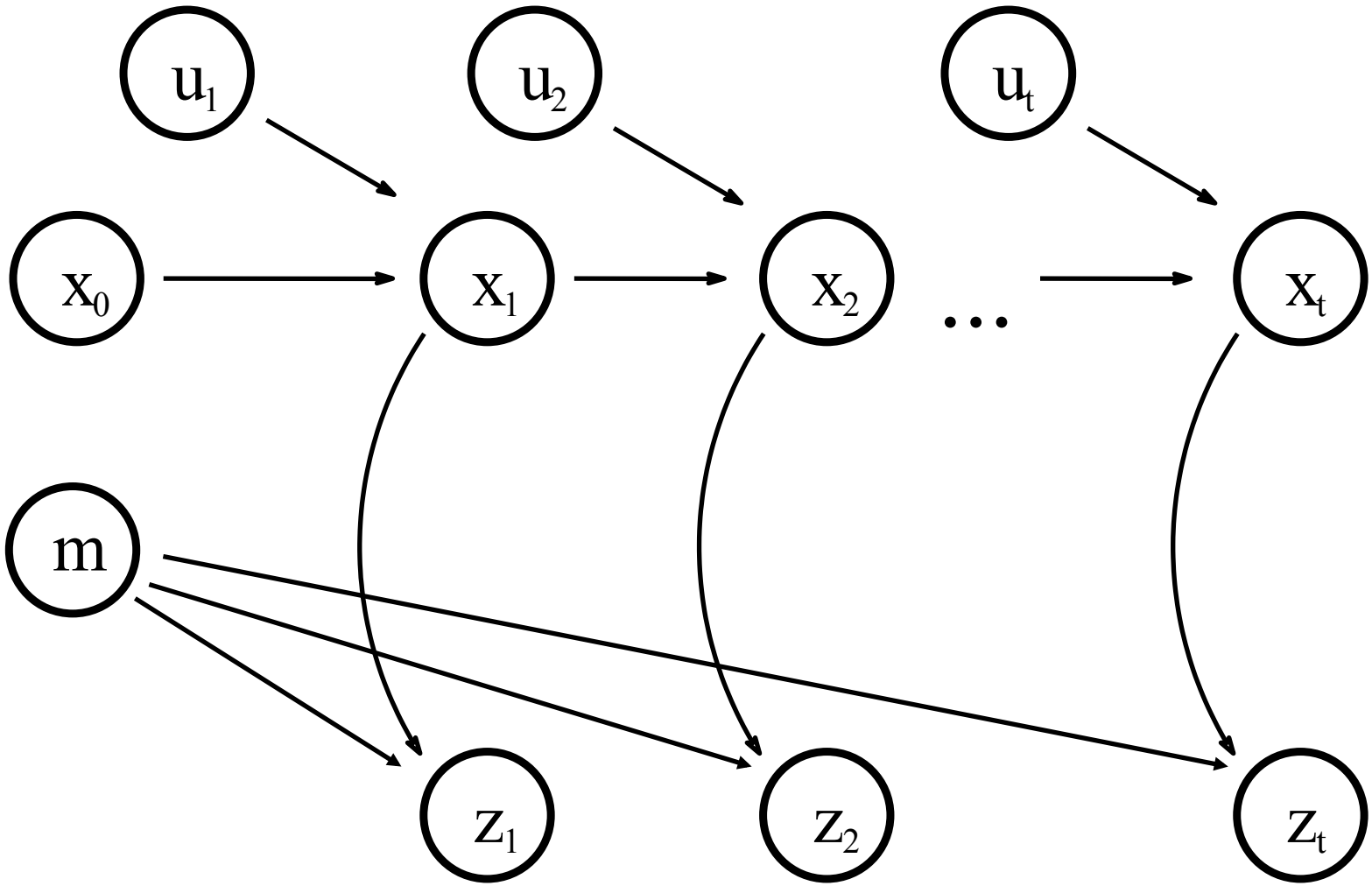
Mapping is a Key Technology for Mobile Robots

- Robots can robustly navigate **when they have a map**.
- Robots have been shown to being able to **deal with a substantial amount of dynamics given a map.**
- An improvement can be expected once robot can **dynamically update their maps**

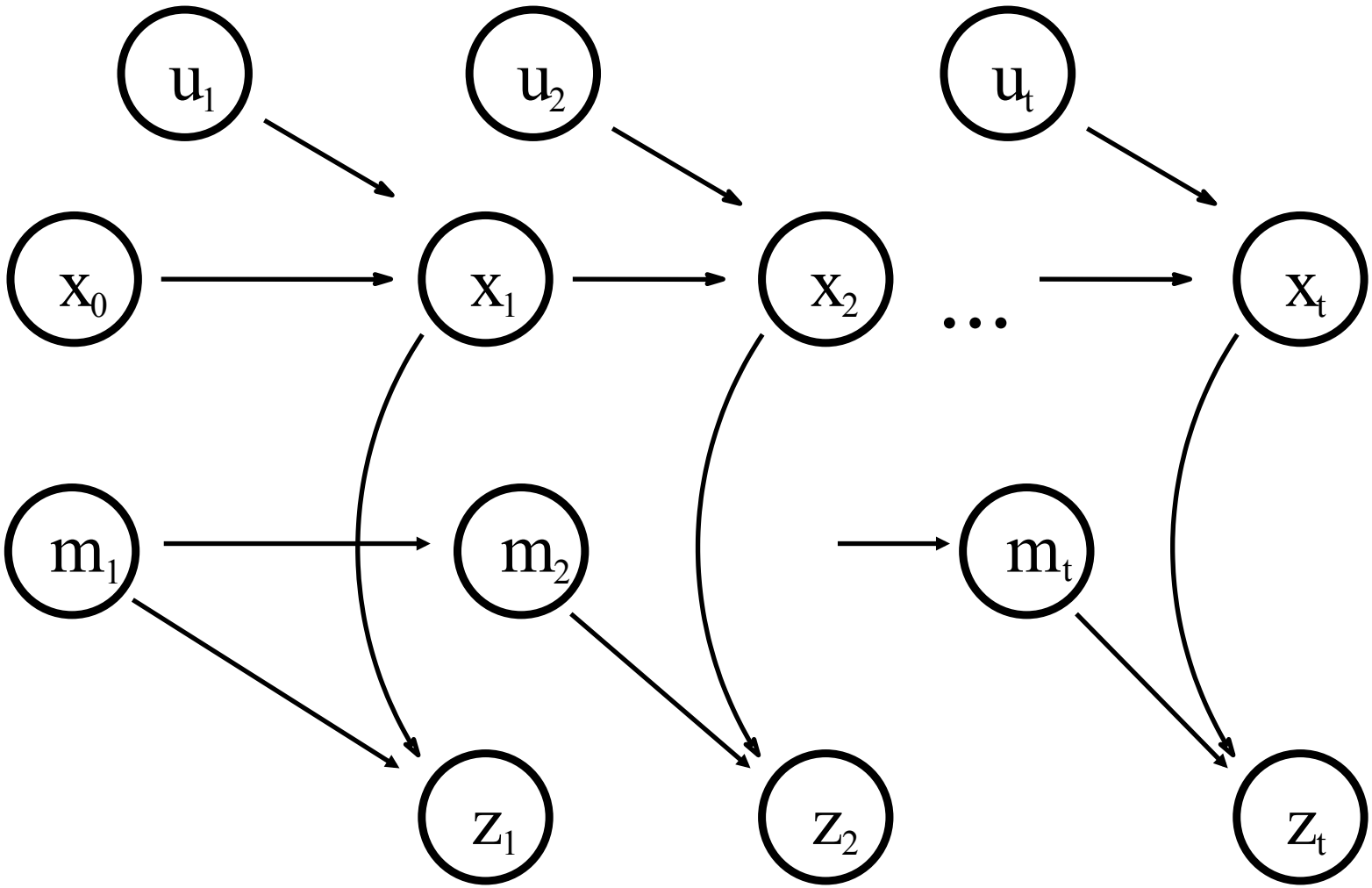
Simultaneous Localization and Mapping (SLAM)

- SLAM enables a robot to **simultaneously estimate its position and map**.
- Typically the **map is assumed to be static**.
- How can we **extend SLAM to dynamic environments**?

A Graphical Model for SLAM in Static Environments



A Graphical Model for SLAM in Dynamic Environments



Probabilistic Formulation

$$P(m_{1,\ldots,t}, x_{1,\ldots,t} \mid z_{1,\ldots,t}, u_{1,\ldots,t})$$

maps | trajectory | measurements | controls

- Scan matching, …
- EKF, UKF, Particle Filters, …
- Maximum likelihood estimation (GraphSLAM)

Mapping by Filtering

- Idea: Bayes filter over both robot positions and map.

$$Bel(m_t, x_t) = \eta\, p(z_t \mid m_t, x_t) \int\int p(x_t, m_{t-1} \mid x_{t-1}, m_{t-1}, u_{t-1}) Bel(m_{t-1}, x_{t-1}) dm_{t-1} dx_{t-1}$$

- Independence of *m* and *x*:

$$Bel(m_t, x_t) = \eta\, p(z_t \mid m_t, x_t) \int\int p(x_t \mid x_{t-1}, u_{t-1}) p(m_t \mid m_{t-1}) Bel(m_{t-1}, x_{t-1}) dm_{t-1} dx_{t-1}$$

- ~~In static worlds~~:

$$\cancel{Bel(m_t, x_t) = \eta\, p(z_t \mid m_t, x_t) \iint p(x_t \mid x_{t-1}, u_{t-1}) Bel(m_{t-1}, x_{t-1}) dm_{t-1} dx_{t-1}}$$

Dynamic Environments

1. Generally, the map is not static while mapping:
   - People walking by,
   - moving objects.

2. Often the world changes over time:
   - Doors open or close,
   - objects are moved around,
   - plants grow …

3. Typical resulting problems:
   - Bad alignments (localization),
   - spurious objects (mapping)

Approaches to Deal with Dynamic Environments

1. Do nothing
2. Change the sensor model
3. Filtering
4. Modeling

Occupancy Grid Maps

- Introduced by Moravec and Elfes in 1985
- Represent environment by a grid.
- Estimate the probability that a location is occupied by an obstacle.
- Key assumptions
  - Occupancy of individual cells is independent

$$\boxed{\begin{aligned} Bel(m_t) &= P(m_t \mid u_1, z_2 \ldots, u_{t-1}, z_t) \\ &= \prod_{x,y} Bel(m_t^{[xy]}) \end{aligned}}$$

  - Robot positions are known!

Updating Occupancy Grid Maps

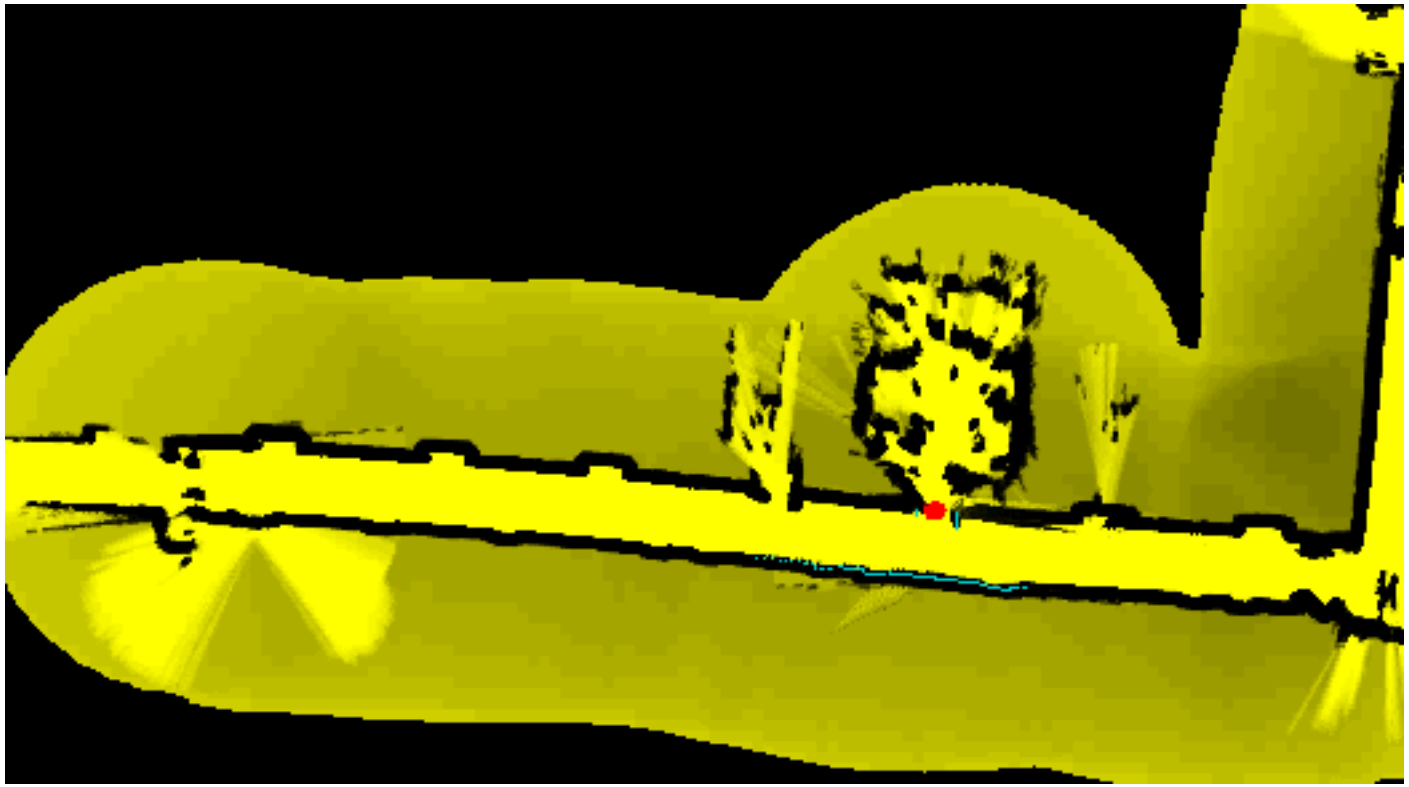
- Typically updated using inverse sensor model and odds ratio:

$$Bel(m_t^{[xy]}) = 1 - \left(1 + \frac{P(m_t^{[xy]} \mid z_t, x_t)}{1 - P(m_t^{[xy]} \mid z_t, x_t)} \frac{1 - P(m_t^{[xy]})}{P(m_t^{[xy]})} \frac{Bel(m_{t-1}^{[xy]})}{1 - Bel(m_{t-1}^{[xy]})}\right)^{-1}$$

- Or log-odds ratio $\overline{B}$:

$$\begin{aligned}\overline{B}(m_t^{[xy]}) = \overline{B}(m_{t-1}^{[xy]}) + \ln P(m_t^{[xy]} \mid z_t, x_t) - \ln\left(1 - P(m_t^{[xy]} \mid z_t, x_t)\right) \\ + \ln\left(1 - P(m_t^{[xy]})\right) - \ln P(m_t^{[xy]})\end{aligned}$$

Using Bayes Rule in Dynamic Environments



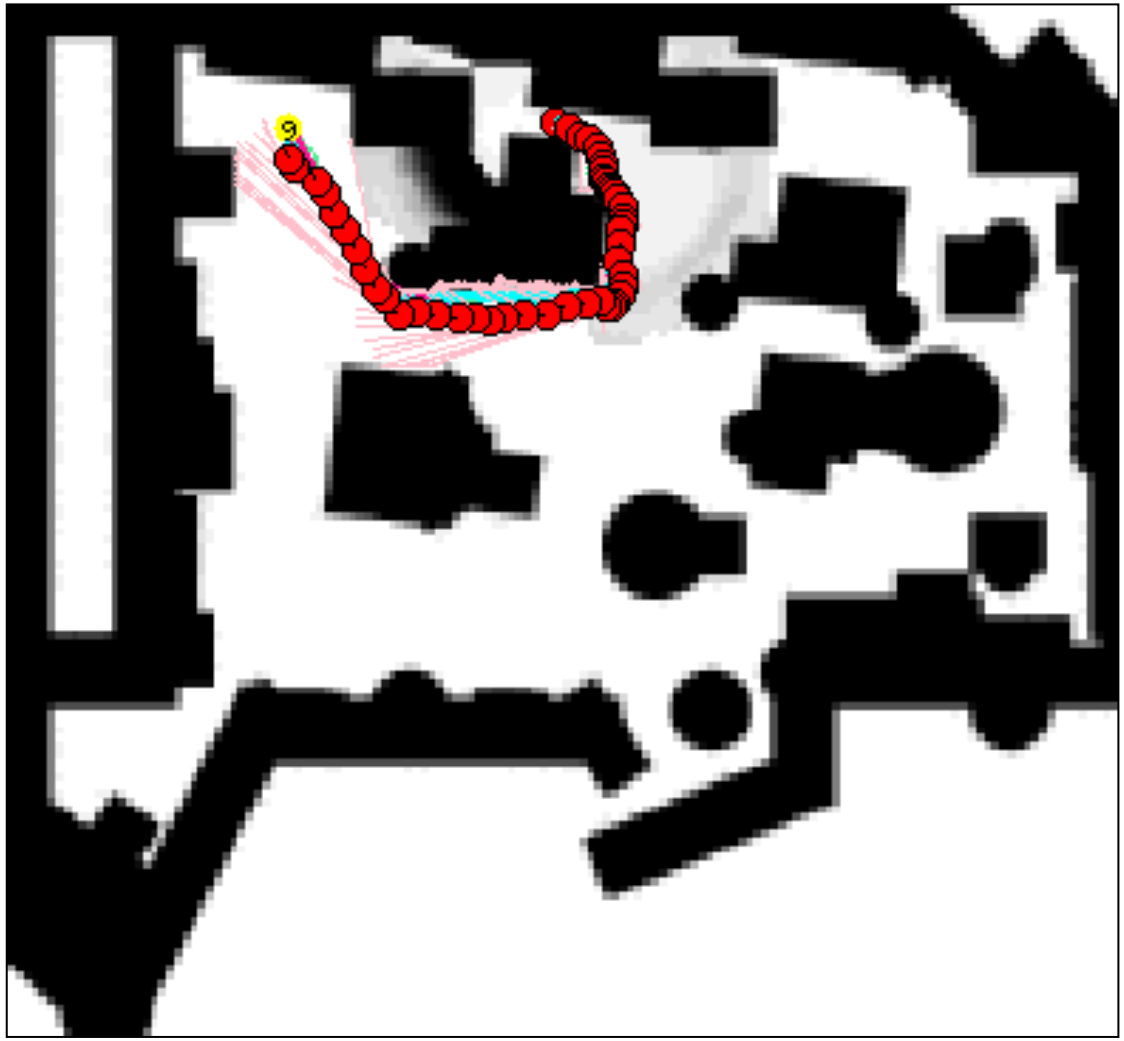
[Avots et al., 2002]

Improvement: Multiple Levels of Maps

- Use a fixed map to represent the static aspects only.
- Use a map learned on the fly to represent the current state of the world.
- Combine both maps using a conservative strategy:

$$Bel(m_t^{[x,y]}) = \max\left(Bel_{static}(m^{[x,y]}), Bel_{dynamic}(m_t^{[x,y]})\right)$$

Works Well in Practice



Example: On-line Mapping with Rhino

[Burgard et al., 99]

Modeling Approach: Mapping in Populated Environments

Problem:

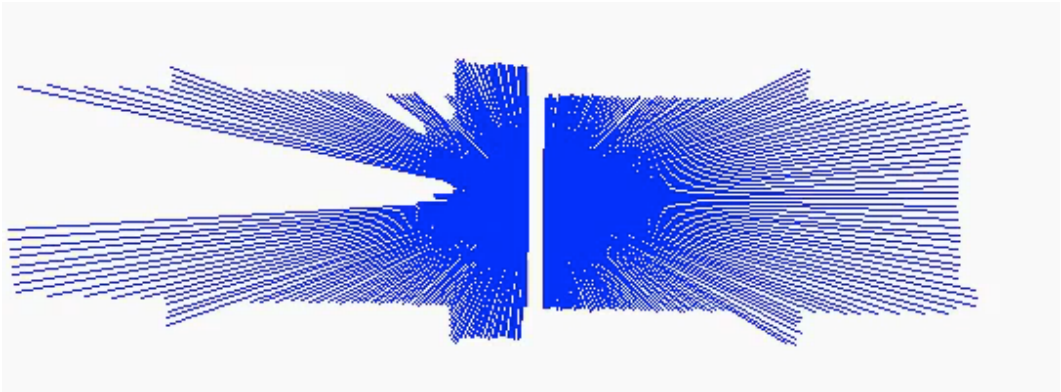
How can we build maps while people are walking through the scene?

Solution:

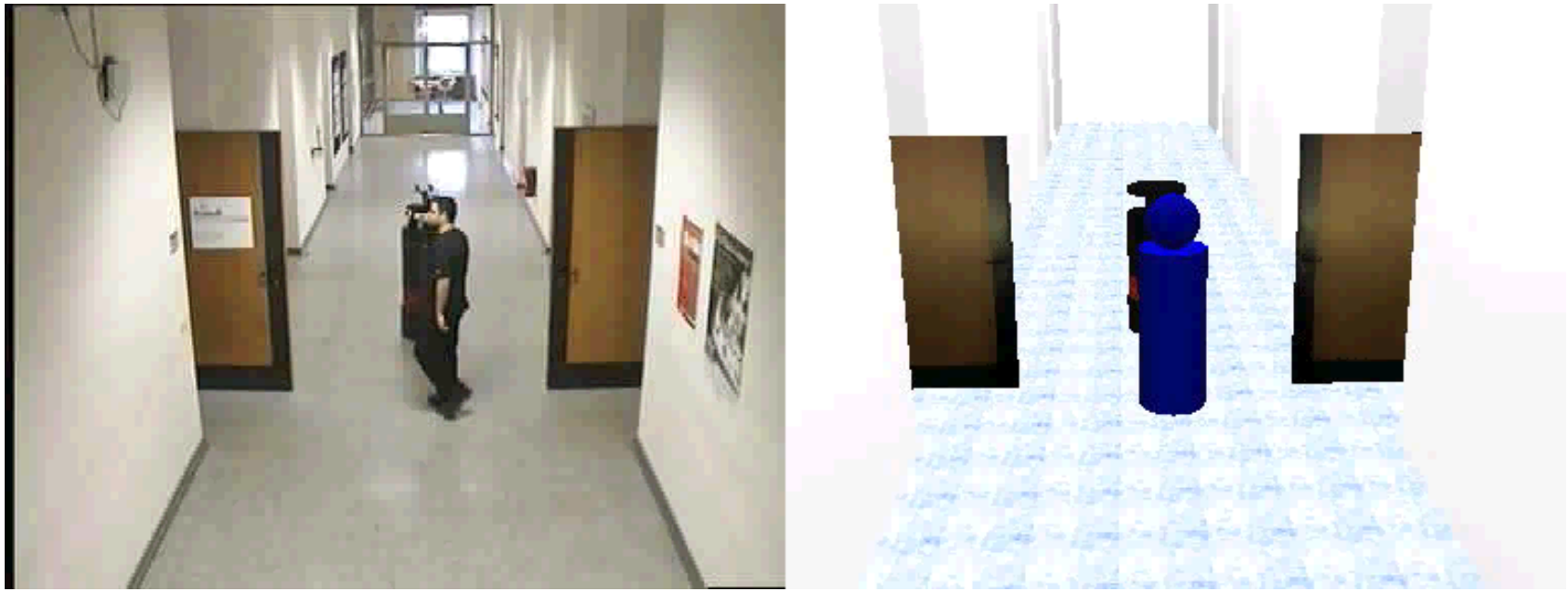
- Feature-based people tracking.
- Appropriately deal with the corresponding beams during localization and map updating.

Problem Description

- **Key questions**
  - How many people are there?
  - Where do they go?
- **Requirements**
  - Real time
  - Eventually no model of the environment
  - Robot in motion

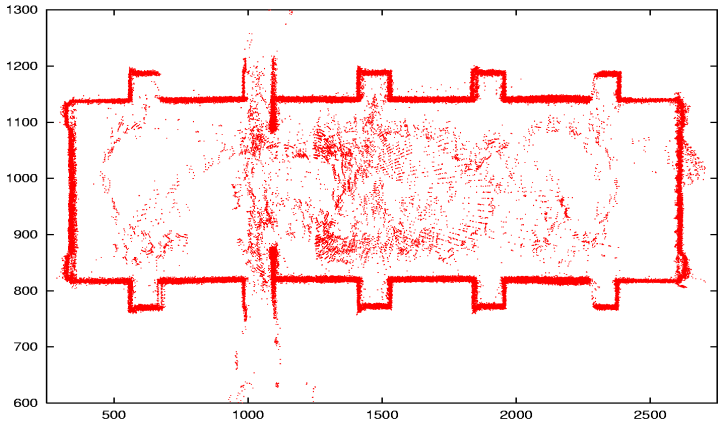


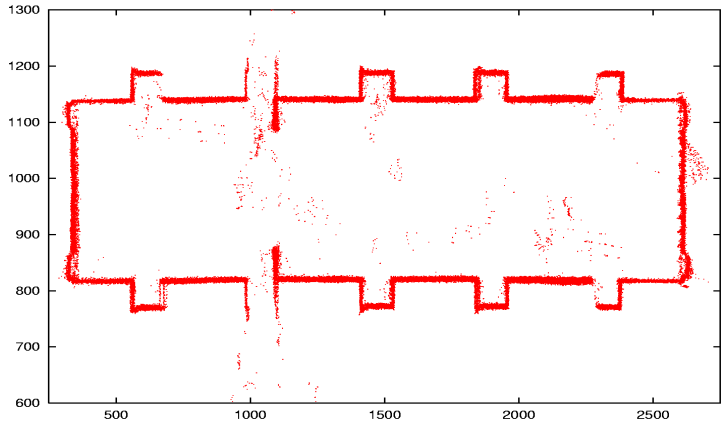
Tracking with a Moving Robot



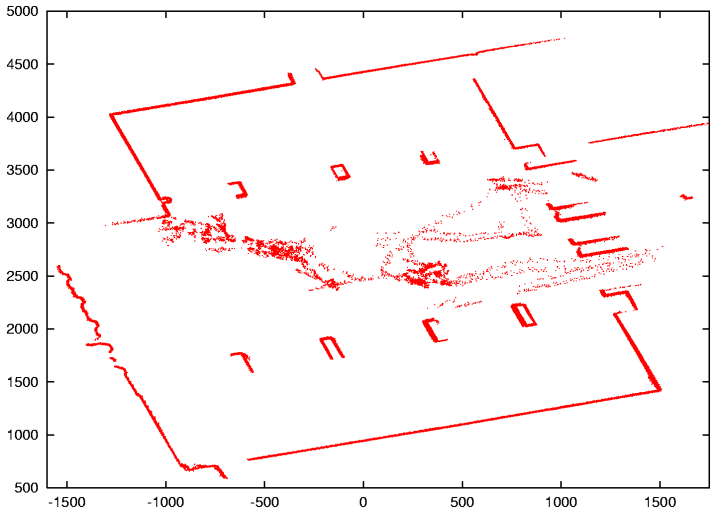
[Schulz et al., 01]

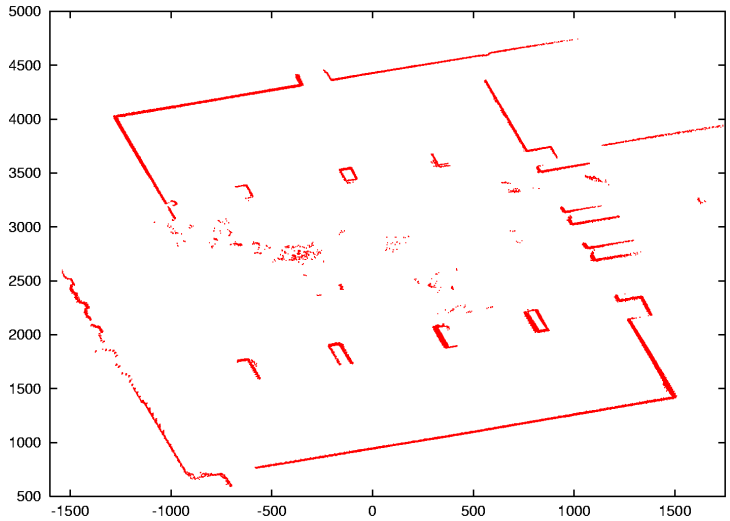
Removing People Detections





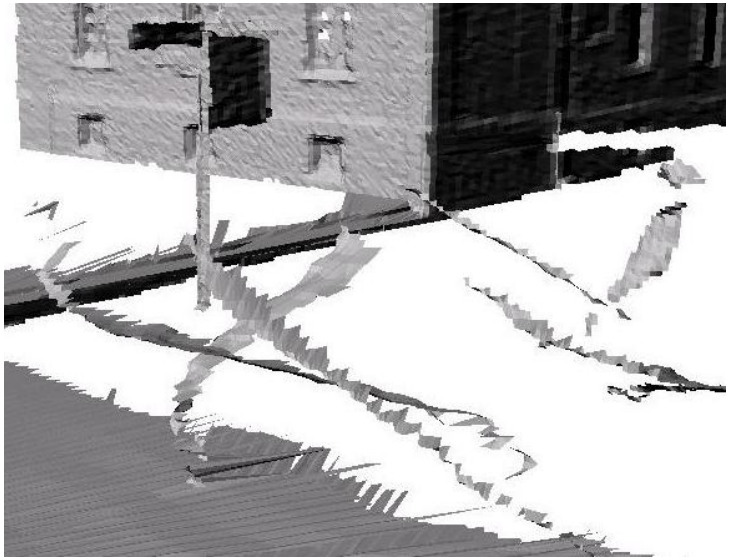
University of Bonn



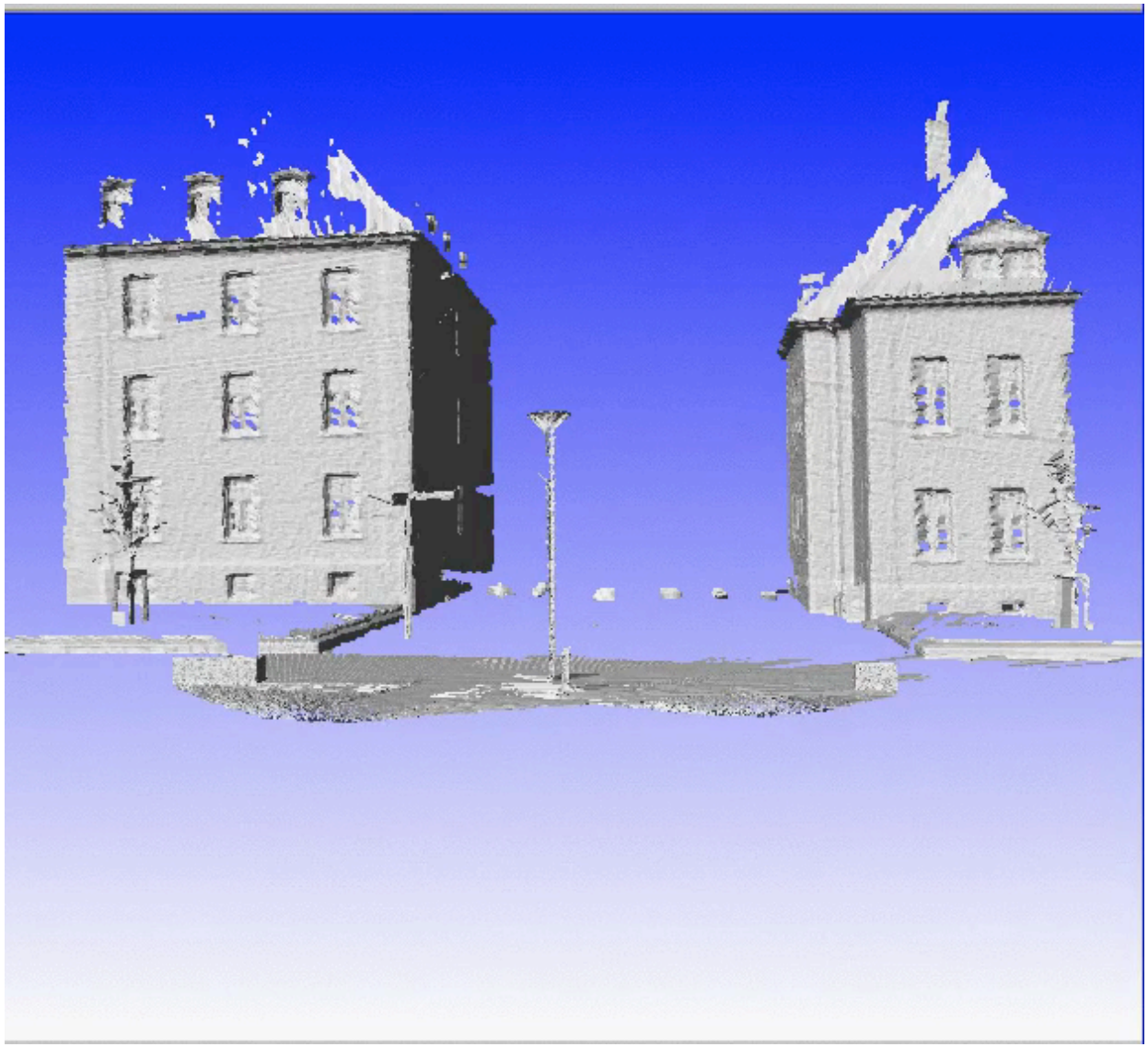


Byzantine Museum, Athens

3D Maps in Populated Environments



A Fly-Through



Filtering Approach to Mapping in Dynamic Environments

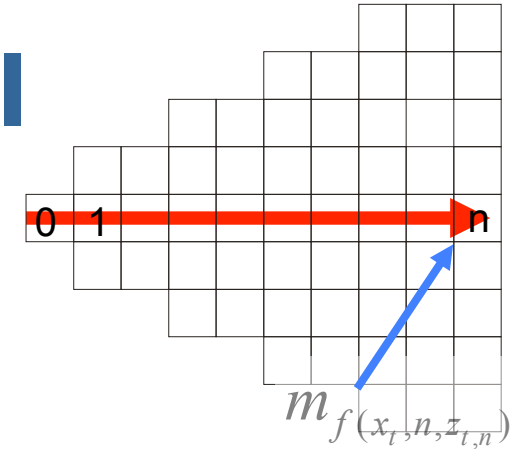
Problem:

- Often models of non-stationary objects are not available.
- Often we cannot assume that there is a separation between non-stationary and static objects.

Solution:

- Using EM to learn beams reflected by dynamic objects.

The Measurement Model



1. pose at time *t*: x_t
2. beam *n* of scan *t*: $z_{t,n}$
3. maximum range reading: $\varsigma_{t,n} = 1$
4. beam reflected by dynamic object: $\varsigma_{t,n} = 0 \text{ and } c_{t,n} = 0$
5. beam reflected by static object: $\varsigma_{t,n} = 0 \text{ and } c_{t,n} = 1$

$$p(z_{t,n} \mid c_{t,n}, x_t, m) = \begin{cases} \prod_{k=0}^{z_{t,n}-1} (1 - m_{f(x_t,n,k)}) & \text{if } \varsigma_{t,n} = 1 \\ \prod_{k=0}^{z_{t,n}} (1 - m_{f(x_t,n,k)}) & \text{if } \varsigma_{t,n} = 0 \text{ and } c_{t,n} = 0 \\ m_{f(x_t,n,z_{t,n})} \prod_{k=0}^{z_{t,n}-1} (1 - m_{f(x_t,n,k)}) & \text{if } \varsigma_{t,n} = 0 \text{ and } c_{t,n} = 1 \end{cases}$$

Application of EM

$$E_c[\ln p(z,c \mid x,m) \mid z,x,m] = N \cdot \sum_{t=1}^{T} E_c[\ln p(c_t)]$$

$$+\sum_{t=1}^{T}\sum_{n=1}^{N}\Big[E_c[c_{t,n} \mid z_{t,n},x_t,m]\cdot(1-\zeta_{t,n})\cdot \ln m_{f(x_t,n,z_{t,n})}$$

$$+(1-E_c[c_{t,n} \mid z_{t,n},x_t,m])\cdot(1-\zeta_{t,n})\cdot \ln(1-m_{f(x_t,n,z_{t,n})}) + \sum_{k=0}^{z_{t,n}-1}\ln(1-m_{f(x,n,k)})\Big]$$

E-Step:

$$e_{t,n} = \begin{cases} \frac{p(c_{t,n}=1|\zeta_{t,n}=1,x_t,m)}{p(c_{t,n}=0|\zeta_{t,n}=1,x_t,m)+p(c_{t,n}=1|\zeta_{t,n}=1,x_t,m)} & \varsigma_{t,n}=1 \\ p(c_{t,n}=1)\cdot\frac{m_{f(x_t,n,z_{t,n})}}{m_{f(x_t,n,z_{t,n})}+(\frac{1}{p(c_{t,n}=1)}-1)\cdot(1-m_{f(x_t,n,z_{t,n})})} & \text{else} \end{cases}$$

M-Step:

Compute most likely map using Bayes rule by considering the expectations $e_{t,n}$ during map updating and localization

Computing the Most Likely Map

$$\hat{m}^{[t]} = \arg\max_{m} \Bigg[\sum_{j=1}^{J} \sum_{t=1}^{T} \sum_{n=1}^{N} \Big(I(f(x_t, n, z_{t,n}) = j)$$

$$\cdot (1 - \varsigma_{t,n}) \cdot (e_{t,n} \ln m_j + (1 - e_{t,n}) \ln(1 - m_j))$$

$$+ \sum_{k=0}^{z_{t,n}-1} I(f(x_t, n, k) = j) \cdot \ln(1 - m_j) \Big) \Bigg]$$

Suppose

$$\alpha_j = \sum_{t=1}^{T} \sum_{n=1}^{N} I(f(x_t, n, z_{t,n}) = j) \cdot (1 - \varsigma_{t,n}) \cdot e_{t,n}$$

$$\beta_j = \sum_{t=1}^{T} \sum_{n=1}^{N} \left[I(f(x_t, n, z_{t,n}) = j) \cdot (1 - \varsigma_{t,n}) \cdot (1 - e_{t,n}) + \sum_{k=0}^{z_{t,n}-1} I(f(x_t, n, k) = j) \right]$$

Computing the Most Likely Map

We assume that all cells m_j are independent:

$$\hat{m}^{[t]} = \arg\max_{m} \left(\sum_{j=1}^{J} \alpha_j \ln m_j + \beta_j \ln(1 - m_j) \right)$$

If we set

$$\frac{\partial m}{\partial m_j} = \frac{\alpha_j}{m_j} - \frac{\beta_j}{1 - m_j} = 0$$

we obtain

$$m_j = \frac{\alpha_j}{\alpha_j + \beta_j}$$

Computing the most likely map amounts to counting how often a cell has reflected a measurement.

EM-based Estimation of the Most Likely Map

M-Step: Compute map m based on the expectations e_{tn}

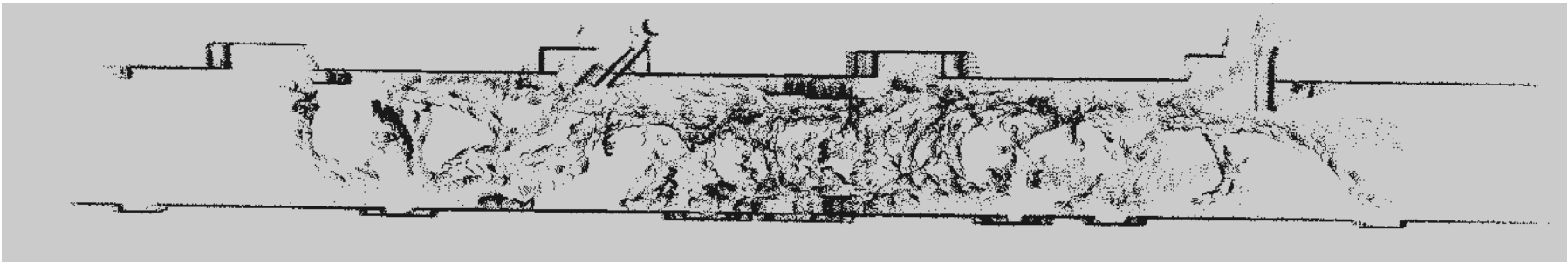
E-Step: Compute the expectation e_{tn} that beam n in scan t is reflected by a dynamic object given m

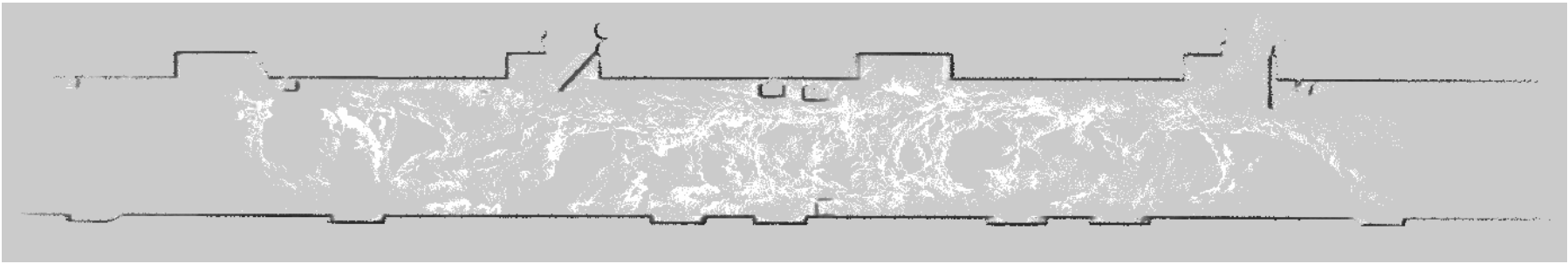
e_{tn}: Expectation that z_{tn} is reflected by a dynamic object

Byzantine Museum, Athens

Wean Hall@CMU

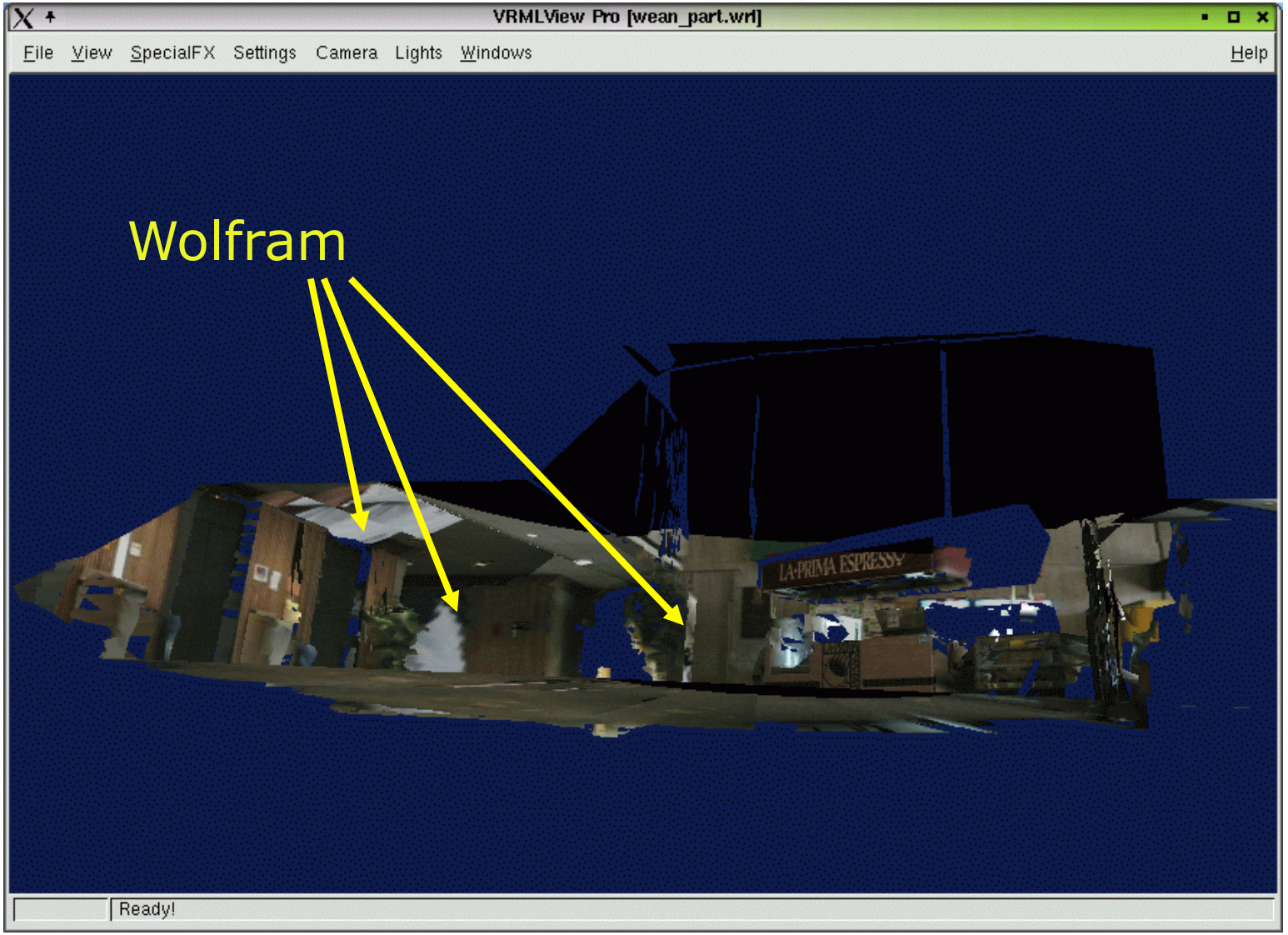
Wean Hall (Hallway)



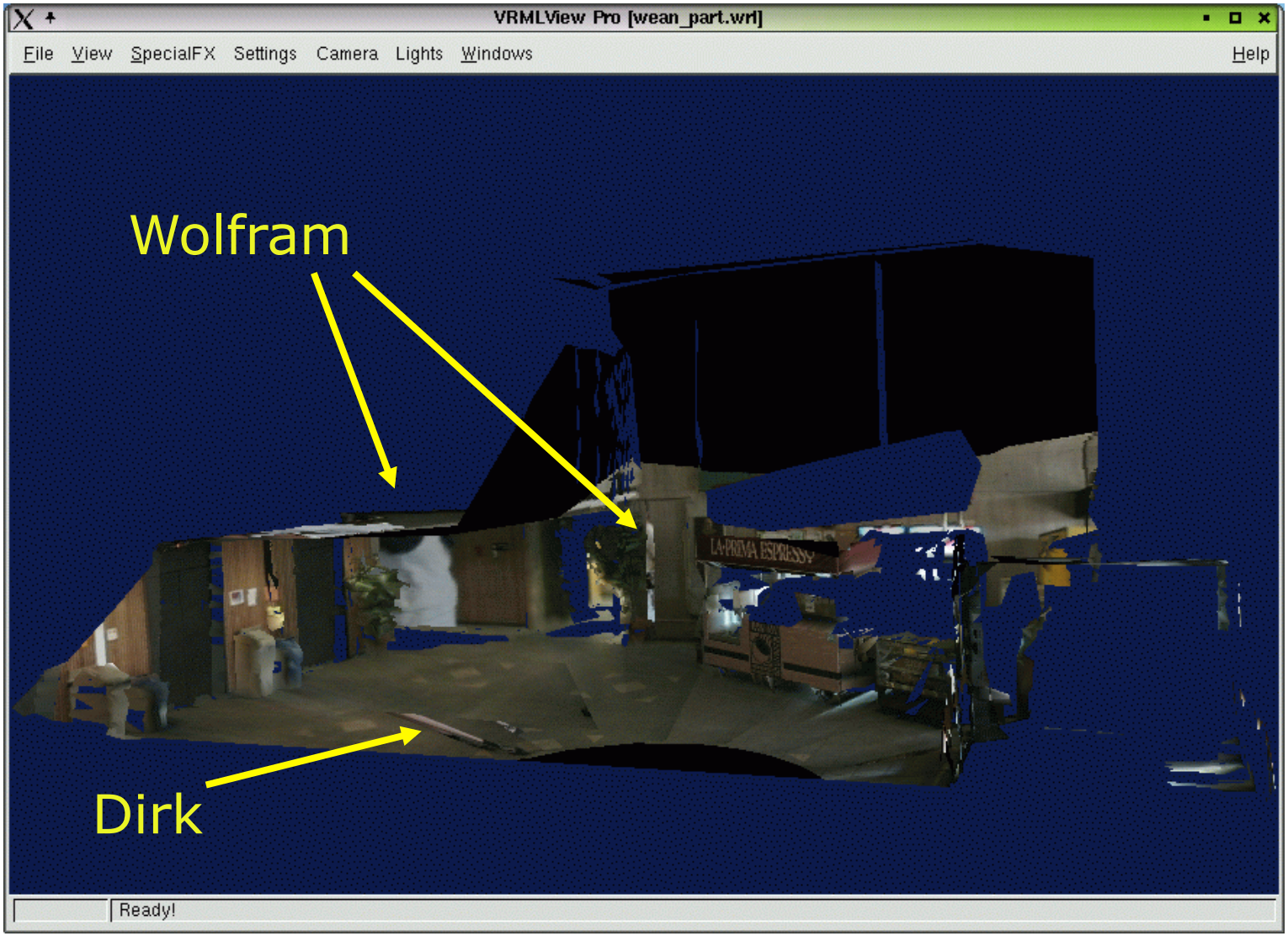


Pittsburgh
Craig Street/Forbes Ave

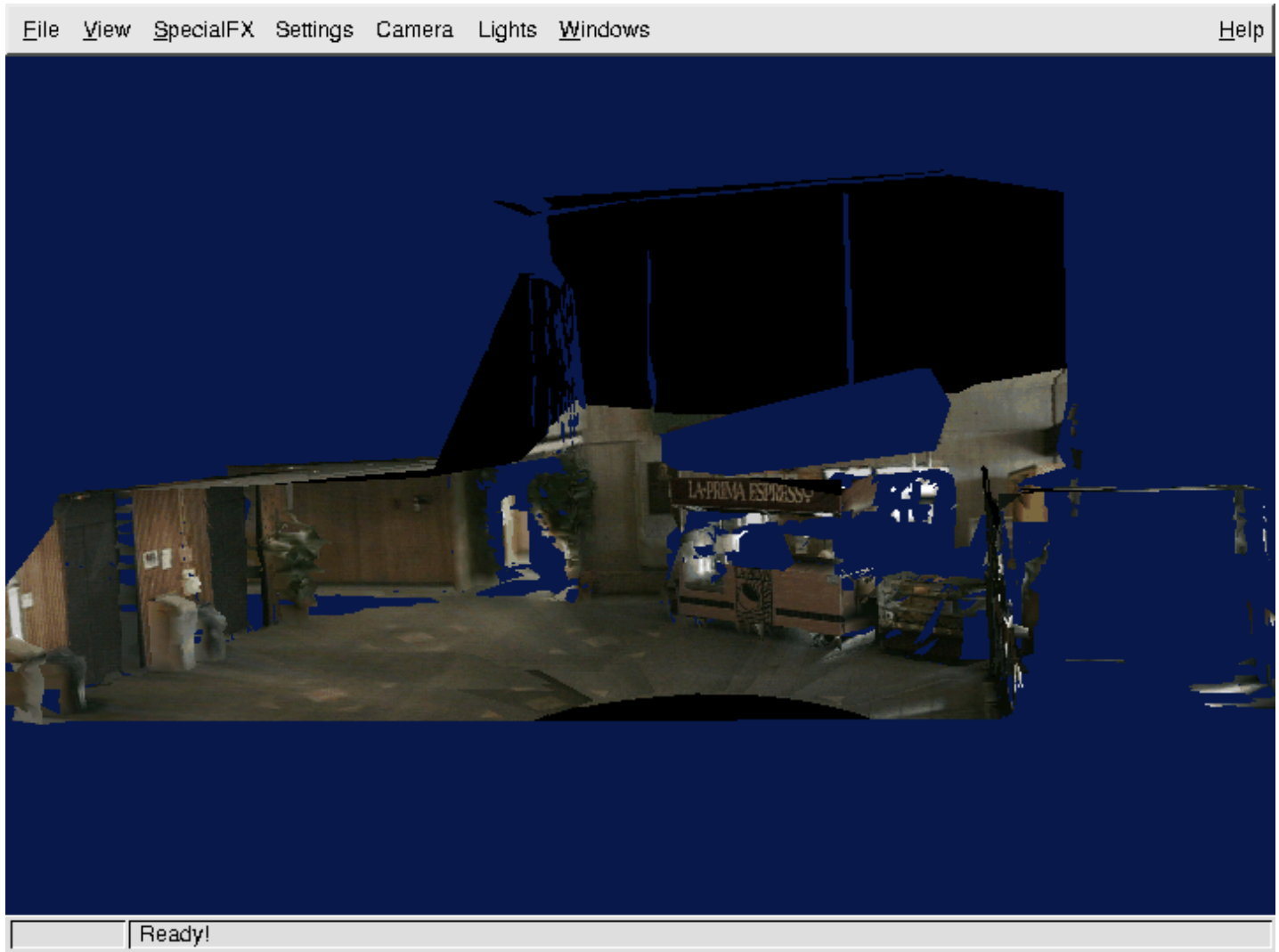
Integrating Laser & Images



Integrating Laser & Images



Resulting Model

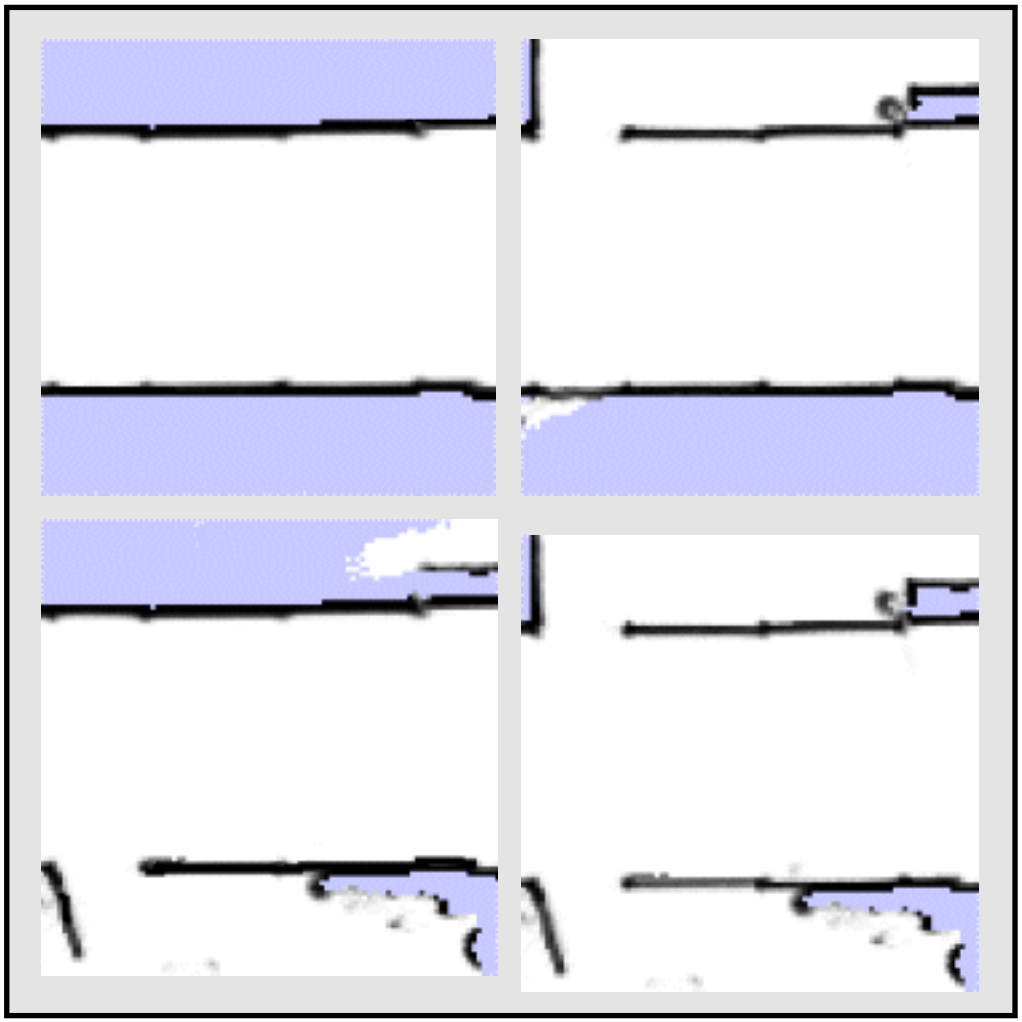


Modeling Low-Dynamics

- Environments are not static
  - Doors can be opened or closed
  - Some objects are moved regularly
- How to model low-dynamic aspects?
- How to use such knowledge to improve the capabilities of a mobile robot?

Door Example

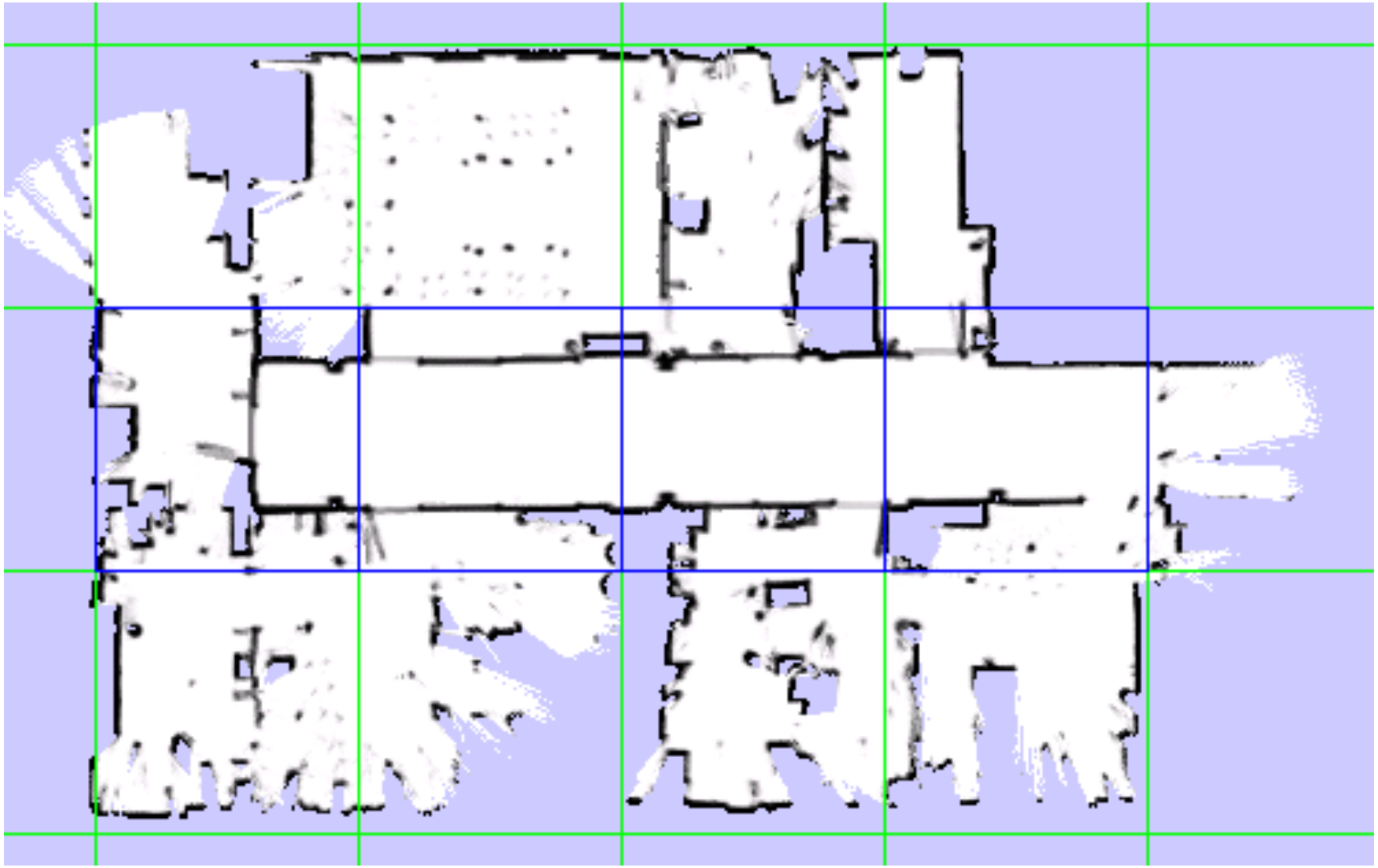
- Possible states in a corridor environment



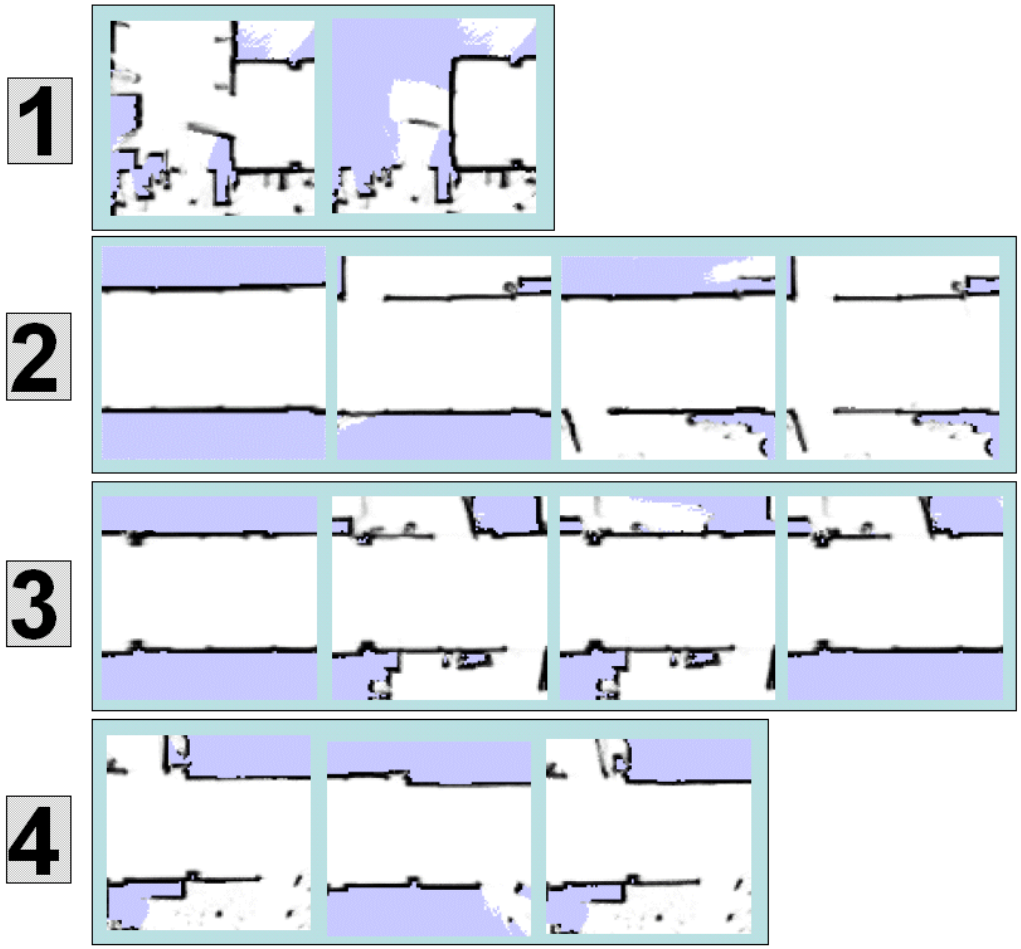
Approach

- Segment the map into sub-maps
- Estimate possible states for each sub-map
- Store the possible configurations in the map
- Use such a representation to improve, e.g., the robot's localization abilities

Mapping Results



Mapping Results

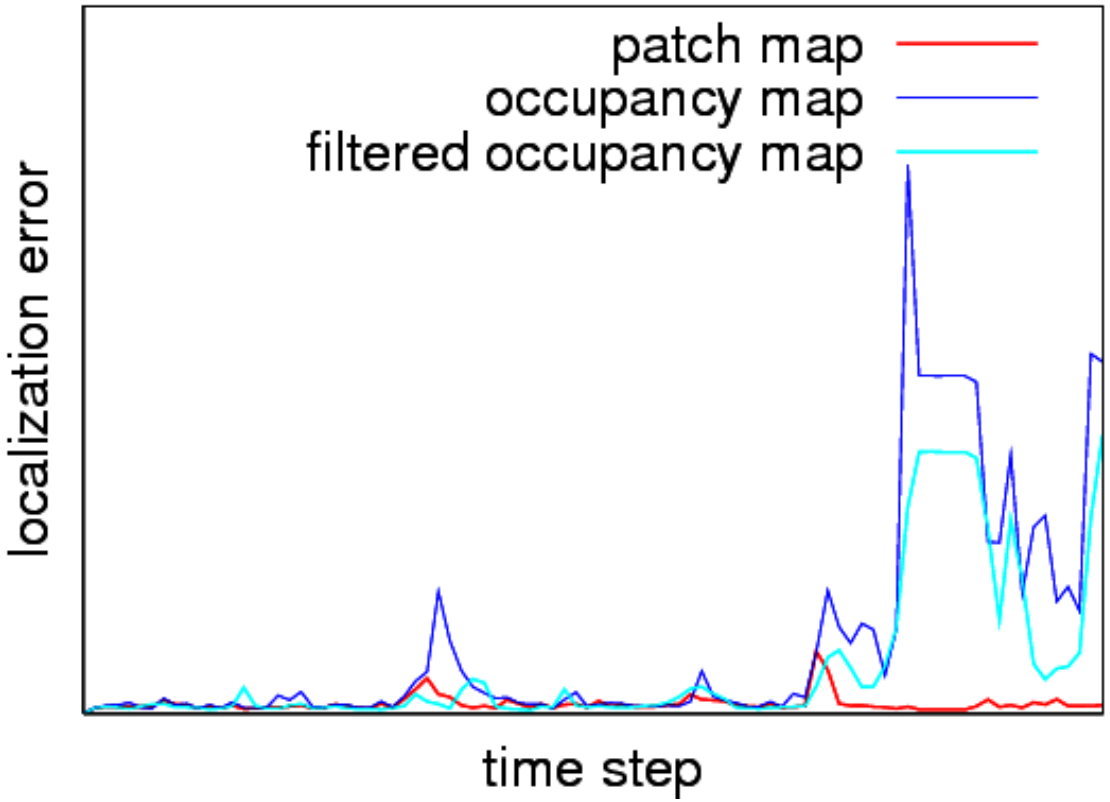


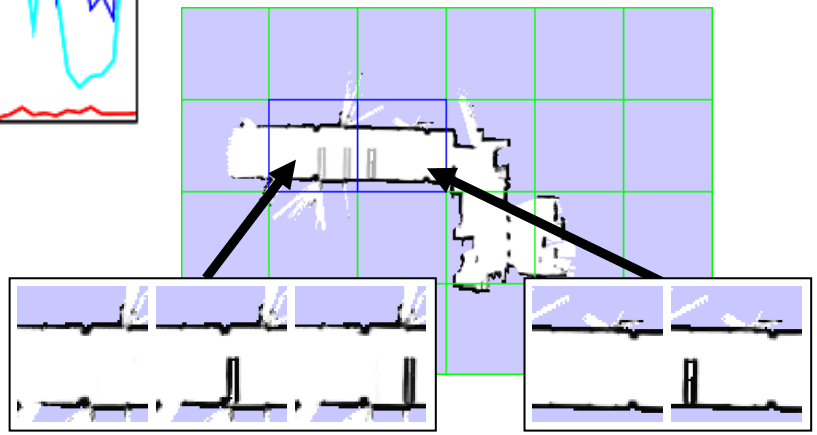
Extended MCL

- Estimate the pose of the robot and the current state of the environment
- We only estimate the state of the current sub-map, the robot is in (sensor provides local information)
- This avoids a large state spaces of the robot (particles):

$$< \underbrace{x, y, \theta}_{\text{robot's pose}}, \underbrace{s}_{\text{sub-map configuration}} >$$

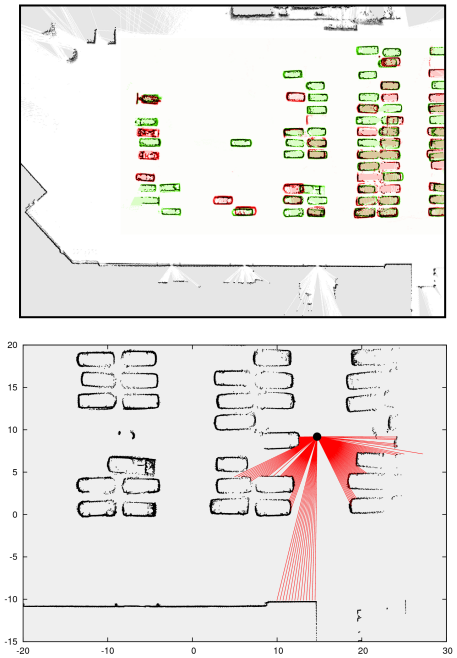
Localization Accuracy Comparison





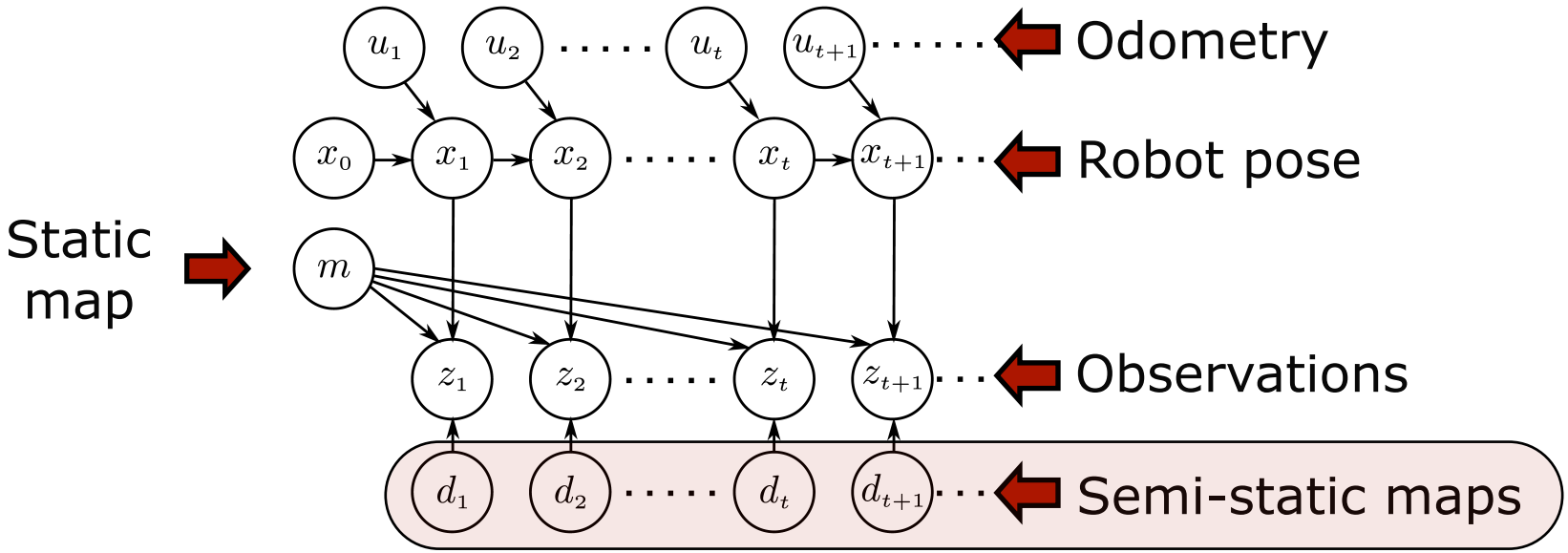
Dynamic Submaps

- What if the variety of the dynamics is too large to allow the clustering approach?
- The alternative is to re-map dynamically depending on the observed changes.
- This allows to localize relative to previously unseen objects



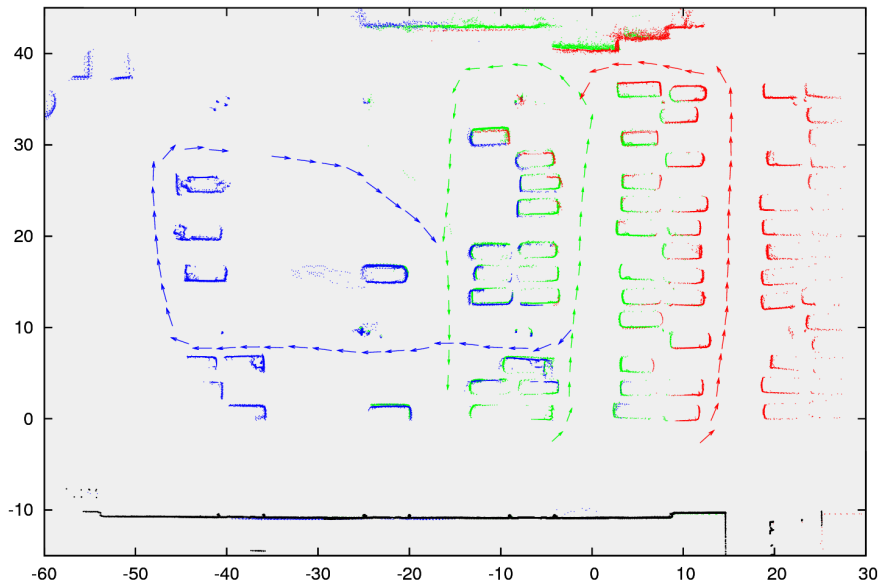
Localization in Semi-static Environments

- Temporary maps represent semi-static objects in the environment
- Observations are caused by both static and semi-static objects



Semi-static Maps

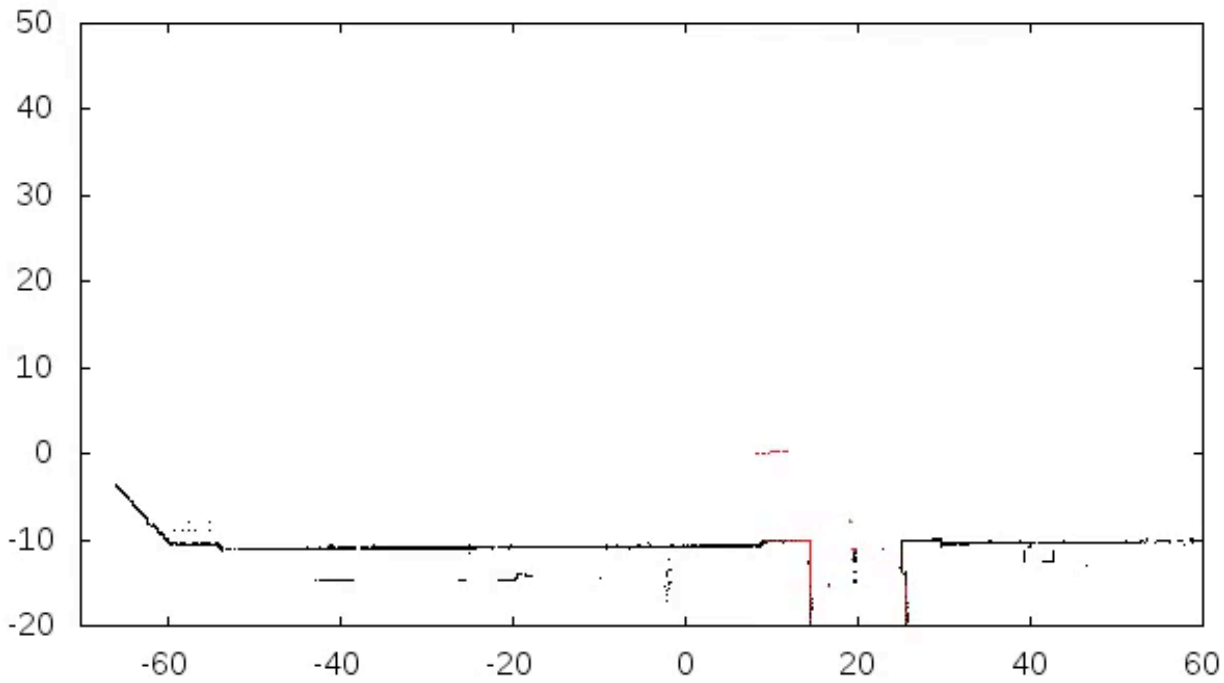
Local map representing semi-static objects as observed by the robot while navigating (*Memory of unexpected observations*)



Static map with three different semi-static maps

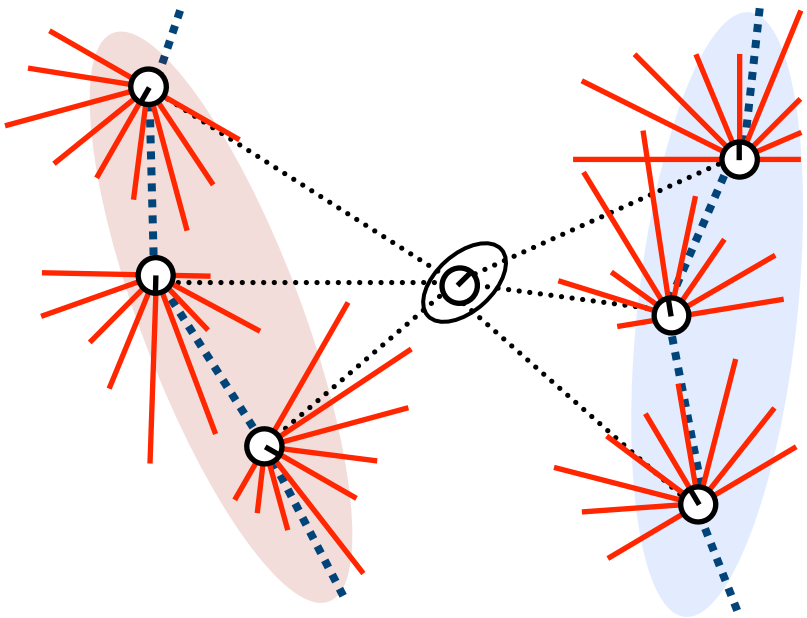
Semi-static Maps

- Represented as pose-graphs
- Constructed from consecutive measurements
- After loop closure we perform optimization



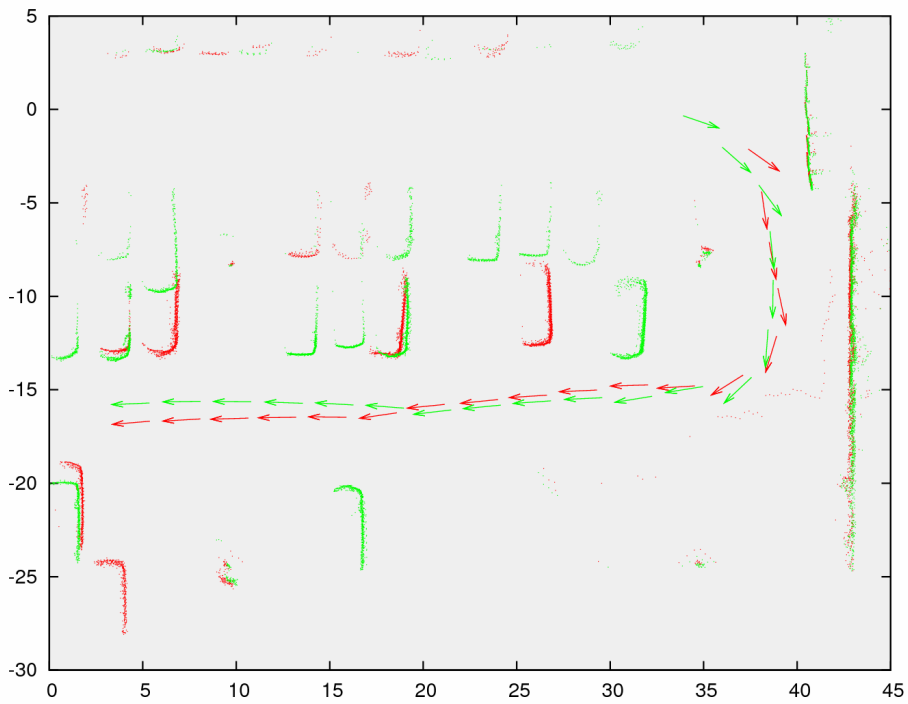
Localization with Temporary Maps

- If observation consistent with static map, use static map for localization
- else select semi-static map for localization.
- Mahalanobis distance for map selection
- If no map is found, we create one

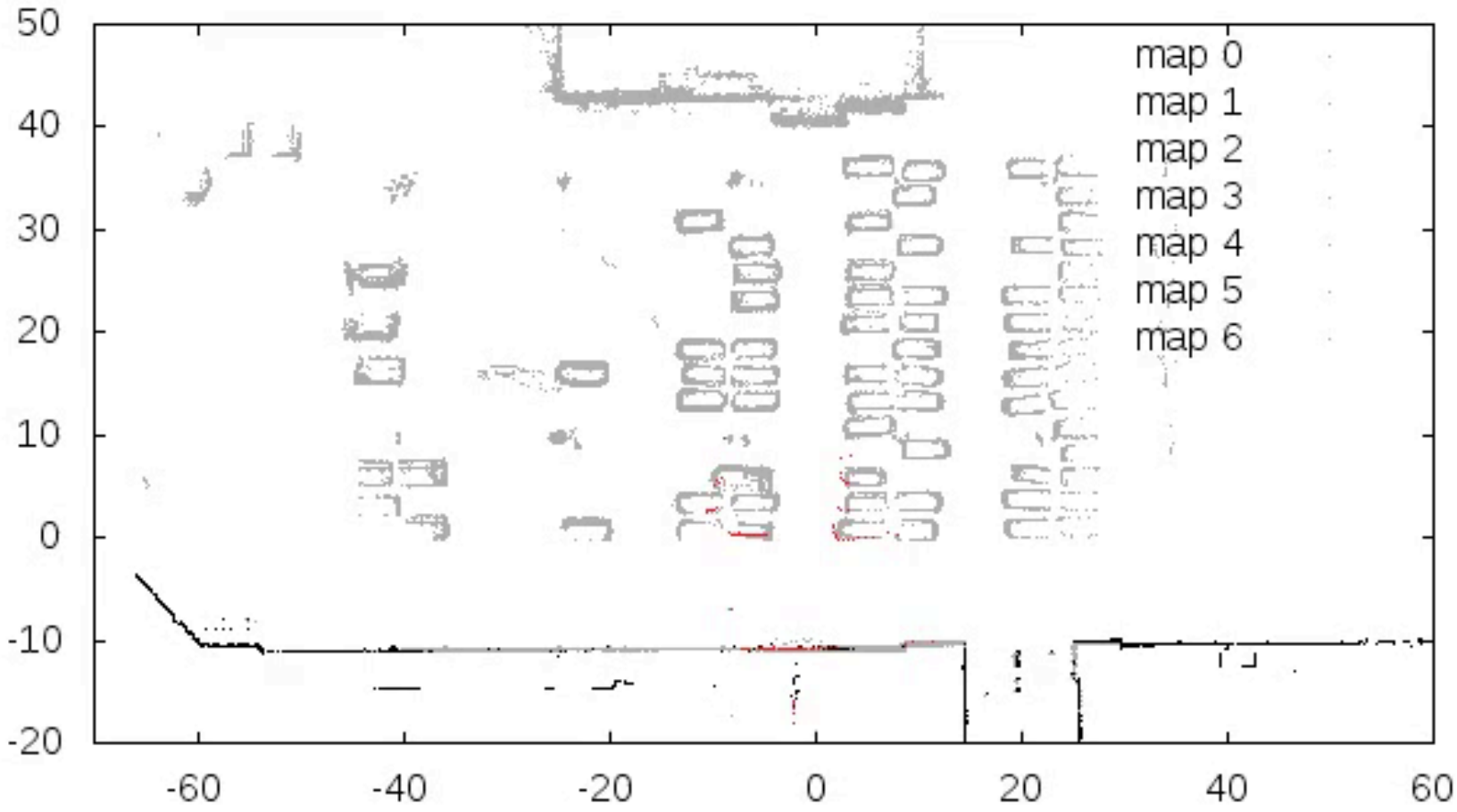


Localization with Temporary Maps

- Semi-static maps are **used if consistent** with the observations.
- **Otherwise** they are **discarded**



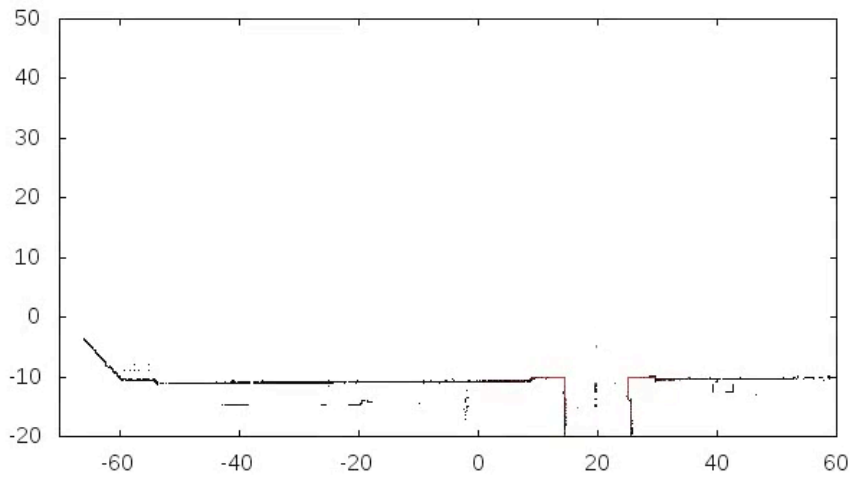
Localization with Temporary Maps



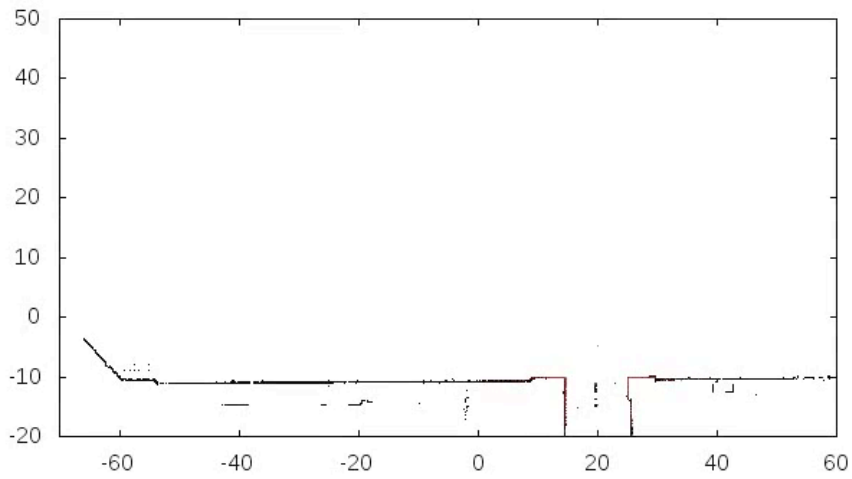
Experiments

Localization in large open spaces

- 30 particles
- Laser max-range set to 20m



Standard particle filter



Temporary maps

Summary

- Different techniques for mapping in dynamic environments
- Object modeling
- Filtering
- Learning sub-map states
- Incrementally updating maps

- The problem is not solved and key for long-term autonomy