POLITECNICO DI MILANO

Cognitive Robotics – SLAM with Lasers

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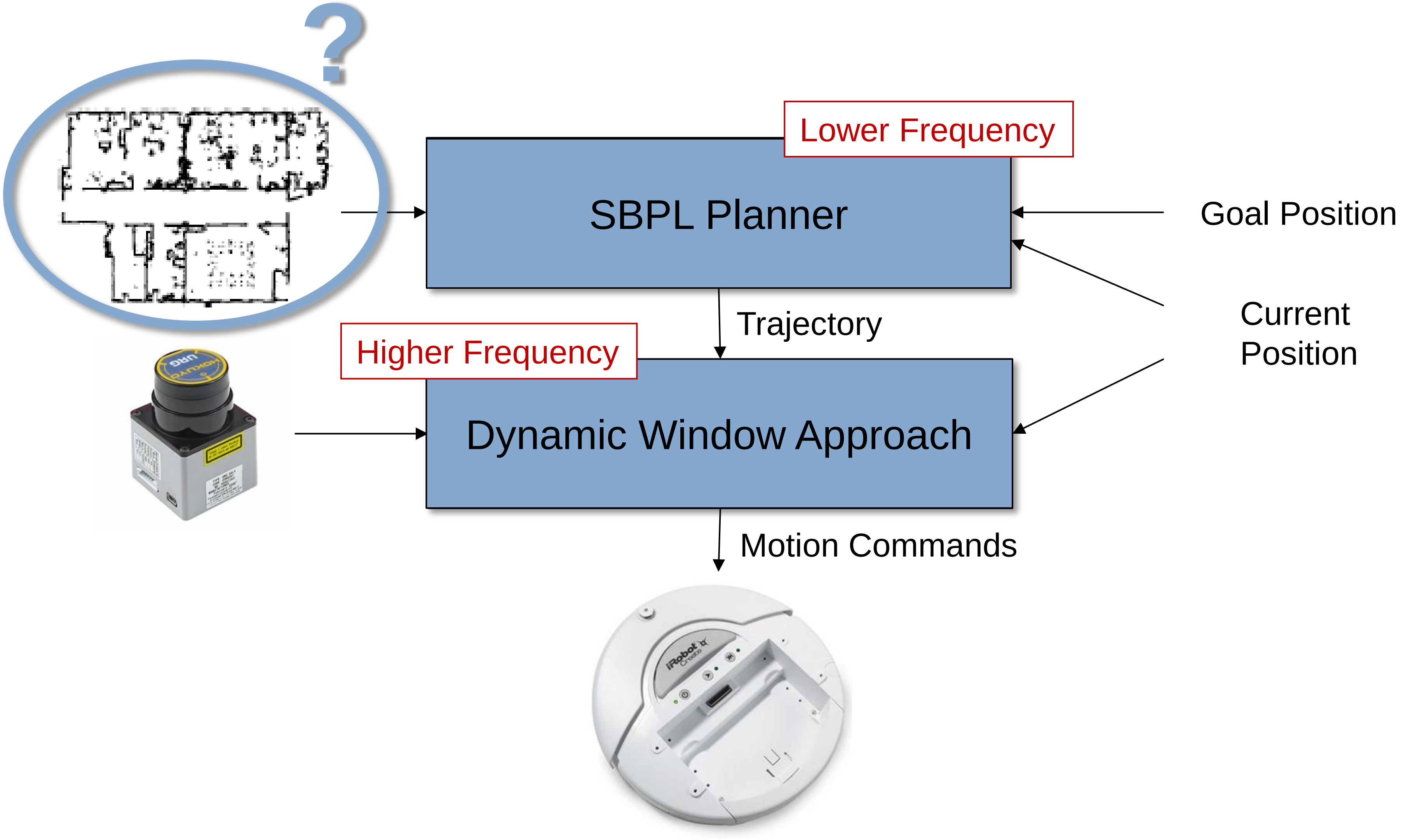
Recall the Two Layered Approach



?

Lower Frequency

SBPL Planner

Goal Position

Trajectory

Current Position

Higher Frequency

Dynamic Window Approach

Motion Commands

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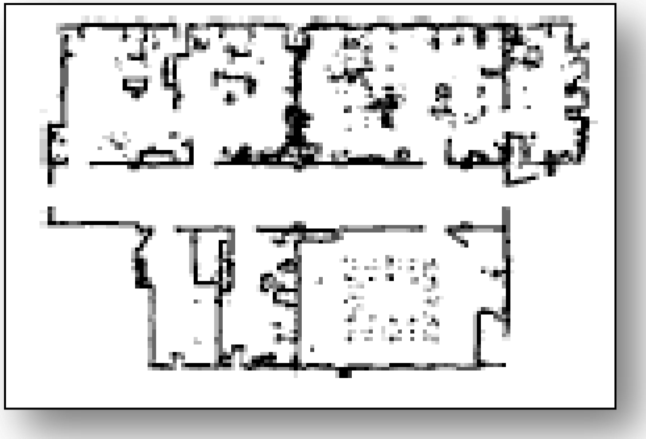
Where Am I?

To perform their tasks autonomous robots and unmanned vehicles need

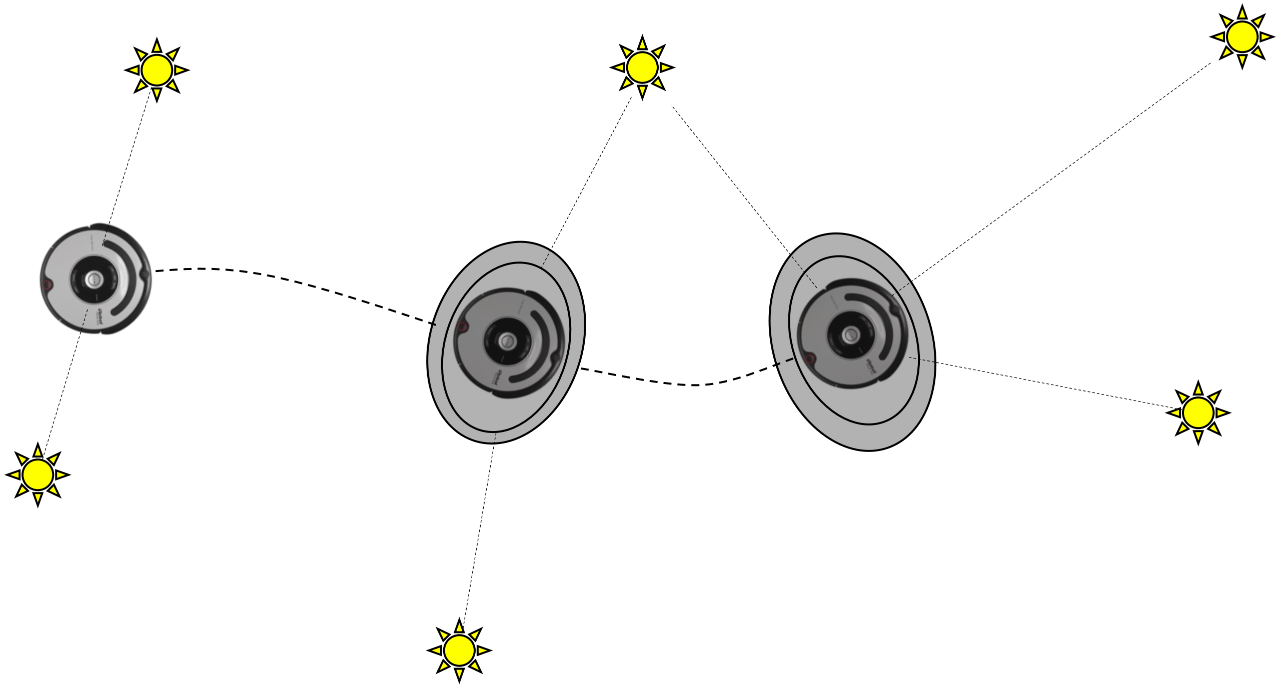
- To know where they are (e.g., Global Positioning System)
- To know the environment map (e.g., Geographical Institutes Maps)

These are not always possible or reliable

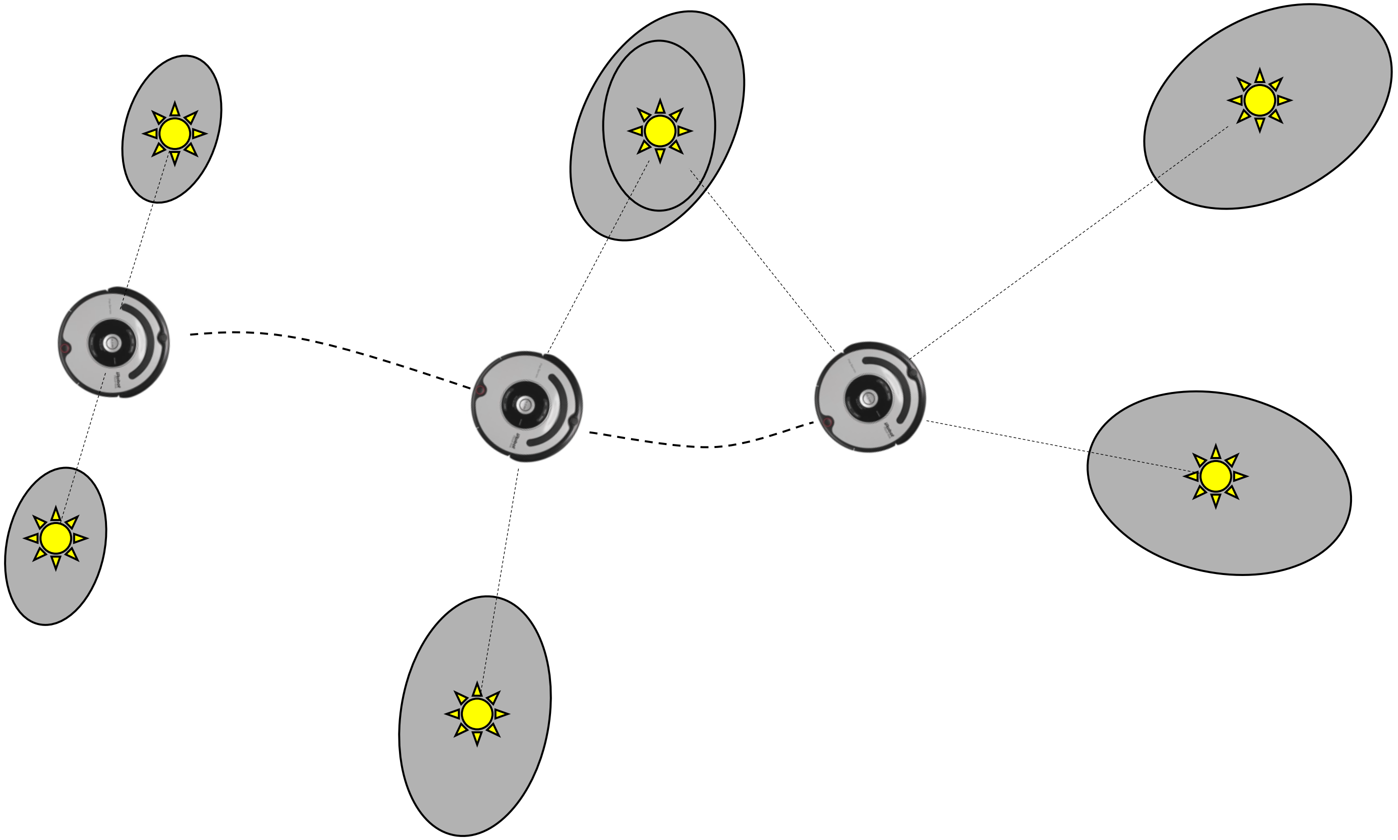
- GNSS are not always reliable/available
- Not all places have been mapped
- Environment changes dynamically
- Maps need to be updated



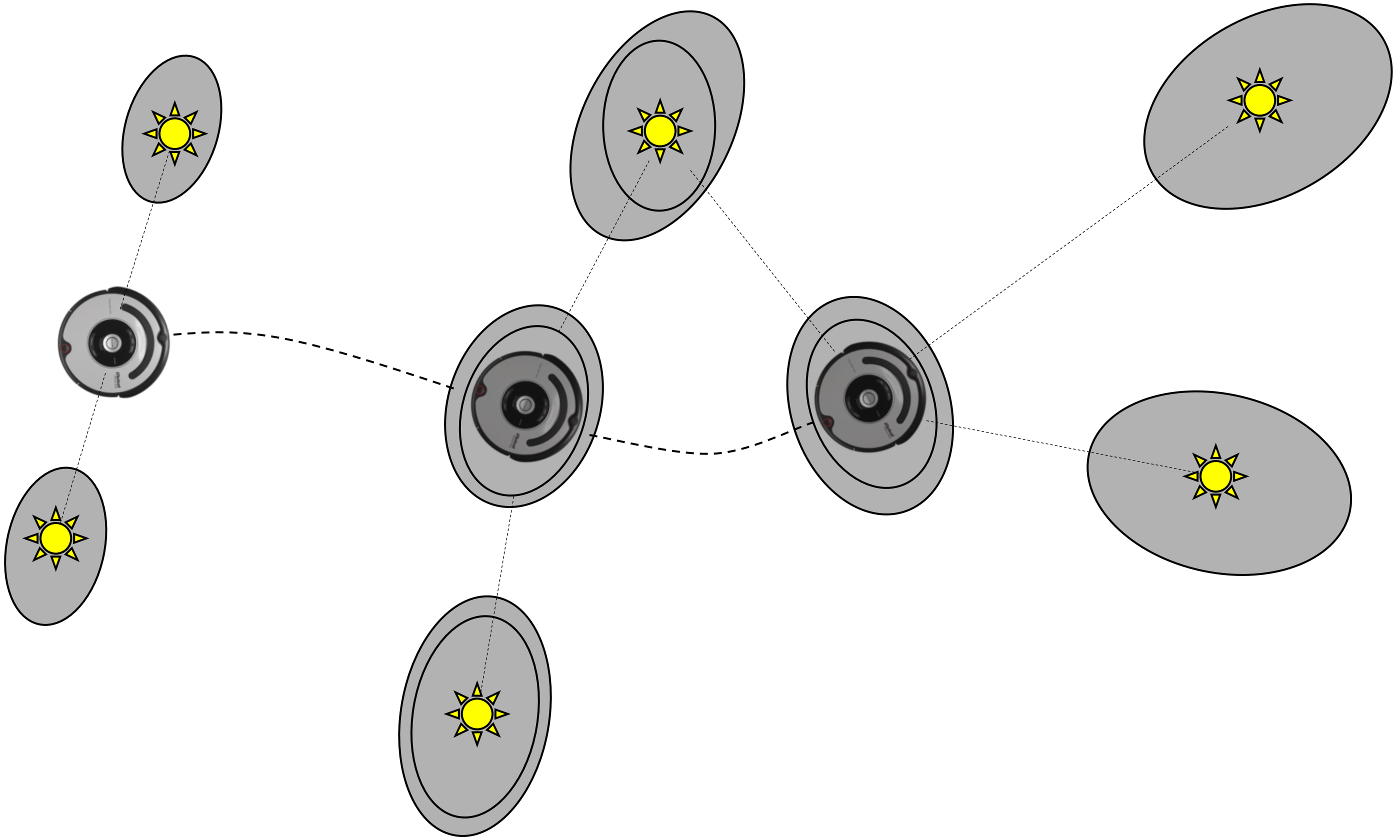
Localization … with known map



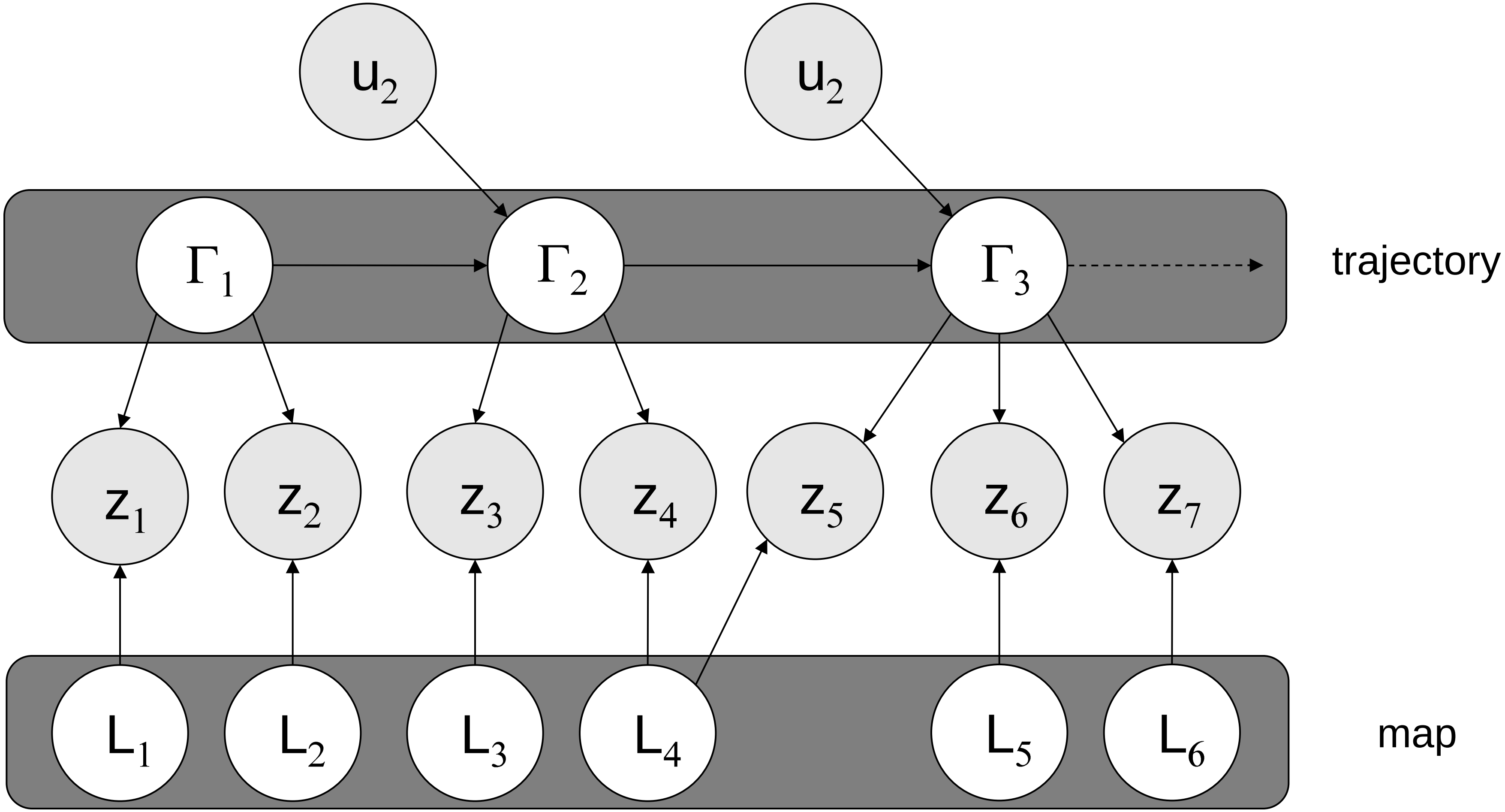
Mapping … with known poses



Simultaneous Localization and Mapping

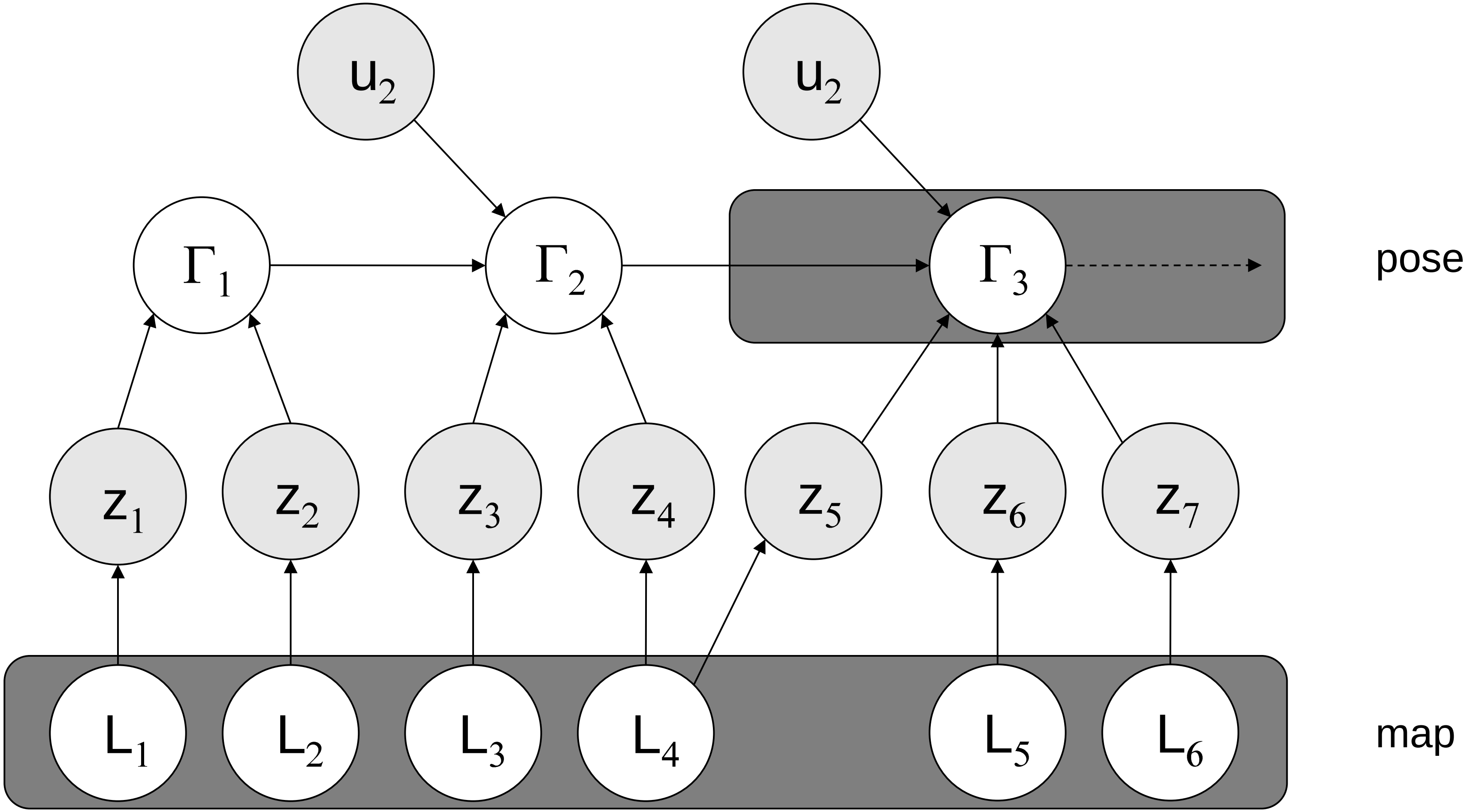


Dynamic Bayes Network Inference and Full SLAM


u_2
u_2
Γ_1
Γ_2
Γ_3
trajectory
z_1
z_2
z_3
z_4
z_5
z_6
z_7
L_1
L_2
L_3
L_4
L_5
L_6
map

Smoothing : $p(\Gamma_{1:t}, l_1, \dots, l_N \mid Z_{1:t}, U_{1:t})$

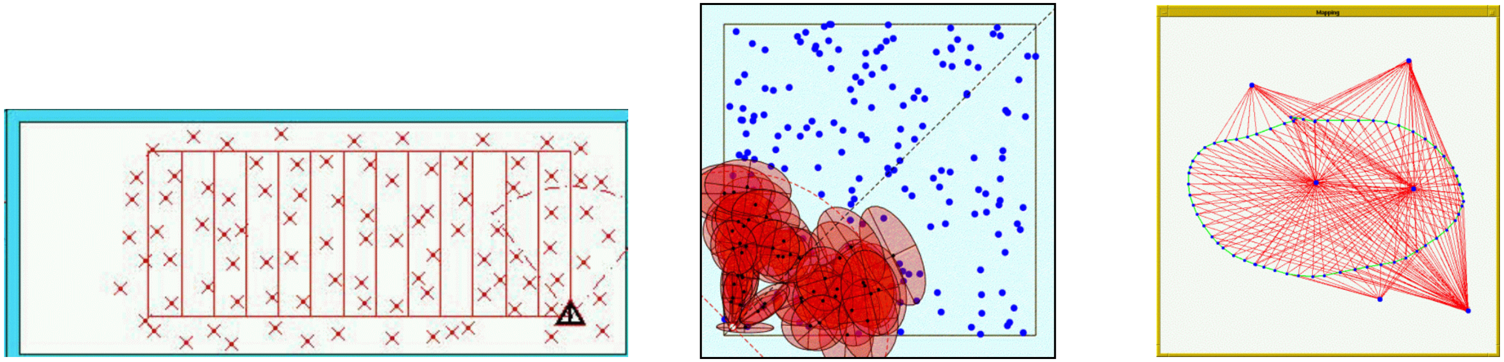
Dynamic Bayes Network Inference and Online SLAM


u₂
u₂
Γ₁
Γ₂
Γ₃
pose
z₁
z₂
z₃
z₄
z₅
z₆
z₇
L₁
L₂
L₃
L₄
L₅
L₆
map

Filtering : $p(\Gamma_t, l_1, \ldots, l_N \mid Z_{1:t}, U_{1:t}) = \iiint_{1:t-1} p(\Gamma_{1:t}, l_1, \ldots, l_N \mid Z_{1:t}, U_{1:t})$

Representations

Landmark-based



[Leonard et al., 98; Castelanos et al., 99: Dissanayake et al., 2001; Montemerlo et al., 2002;…]

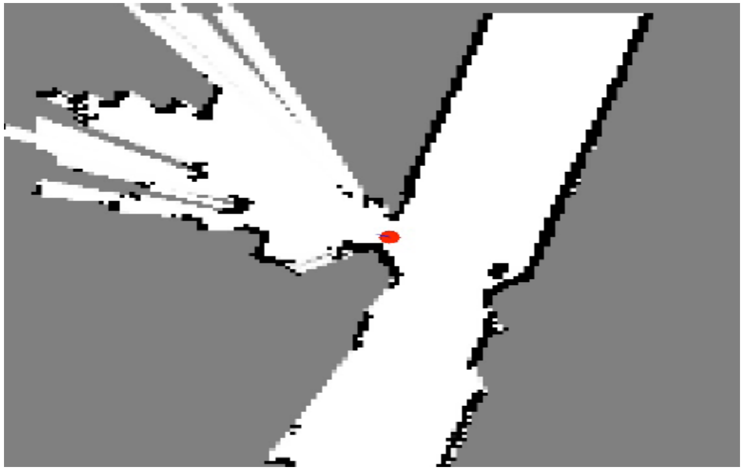
Grid maps or scans

[Lu & Milios, 97; Gutmann, 98: Thrun 98; Burgard, 99; Konolige & al., 00; Thrun, 00; Arras, 99; Haehnel, 01;…]

Occupancy Grids

A simple 2D representation for the map

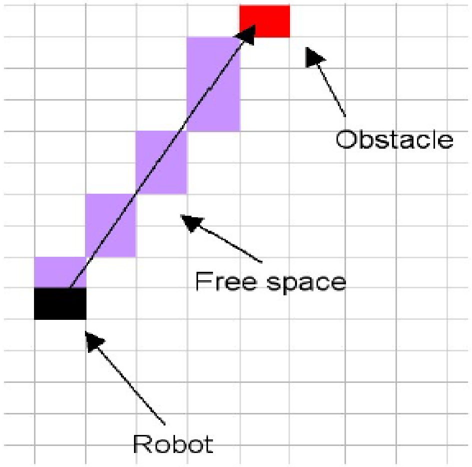
- Each cell is assumed independent
- Probability of a cell being occupied is being estimated through the Bayes theorem



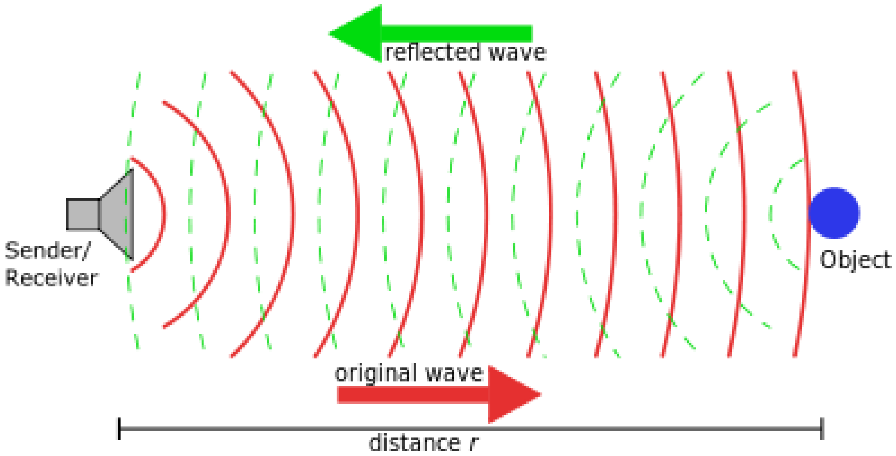
$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} = \frac{P(B|A)P(A)}{P(B|A)P(A) + P(B|\neg A)P(\neg A)}$$

Maps the environment as an array of cells

- Cell sizes range from 5 to 50 cm
- Each cell holds a probability value that the cell is occupied
- Useful for combining different sensor scans, and even different sensor modalities

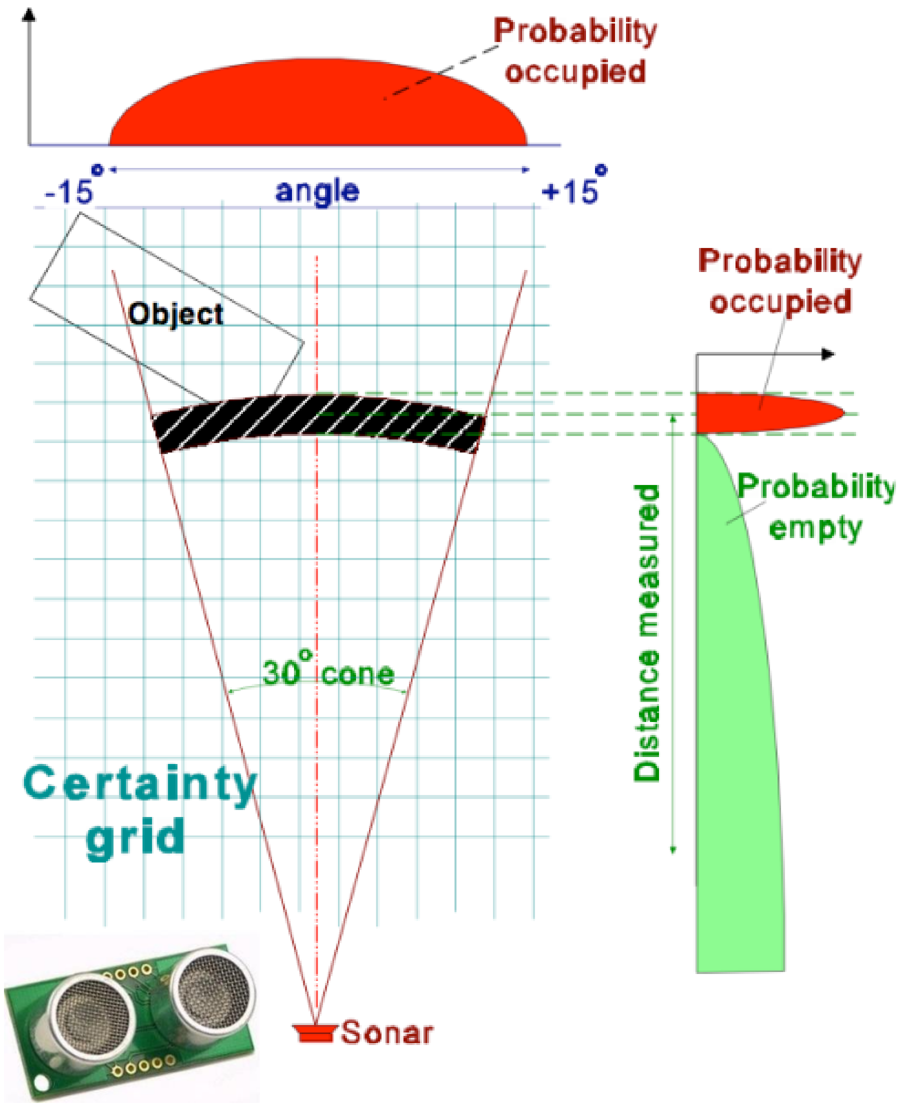


Sonar Sensor Model (Ultrasound Wave)

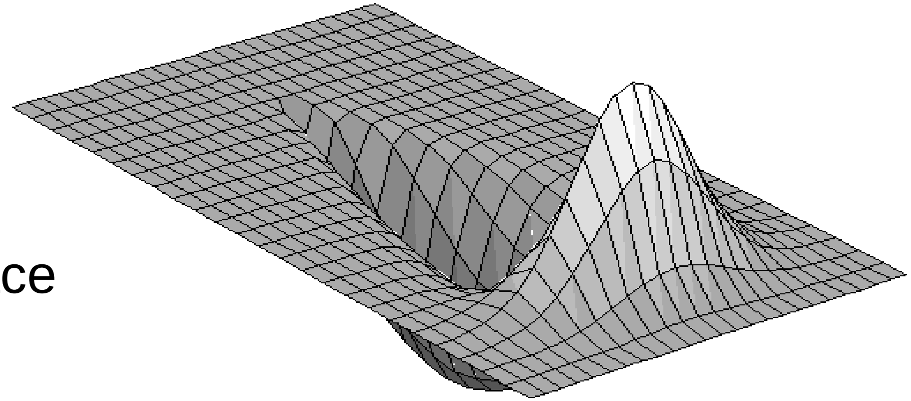

reflected wave
Sender/
Receiver
Object
original wave
distance r

An US wave is sent by a transducer

- Time of flight is measured
- Distance is computed from it
- Obstacle could be anywhere on the arc at distance D
- The space closer than D is likely to be free.


Probability
occupied
-15°
angle
+15°
Object
Probability
occupied
Probability
empty
Distance measured
30° cone
Certainty
grid
Sonar

Occupancy from Sonar Return



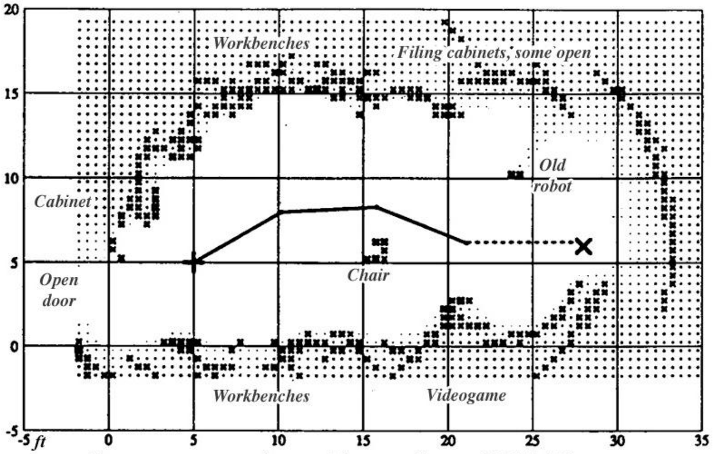
The most simple occupancy model uses

- A 2D Gaussian for information about occupancy
- Another 2D Gaussian for free space

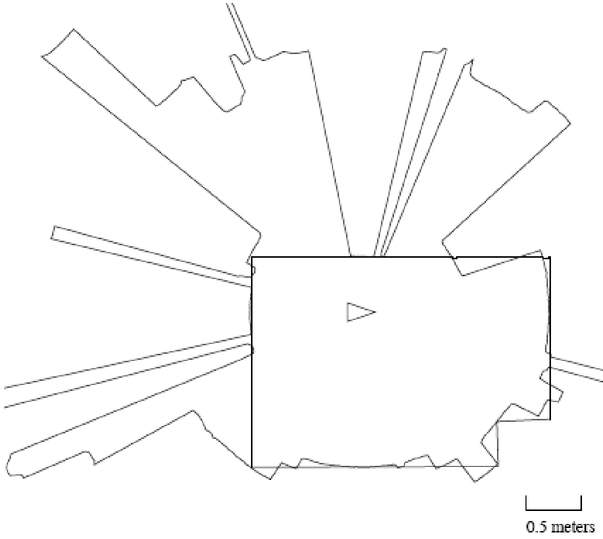
Sonar sensors present several issues

- A wide sonar cone creates noisy maps
- Specular (multi-path) reflections generates unrealistic measurements

Moravec 1984


20
15
10
5
0
-5 ft
0
5
10
15
20
25
30
35
Workbenches
Filing cabinets, some open
Old robot
Cabinet
Open door
Chair
Workbenches
Videogame

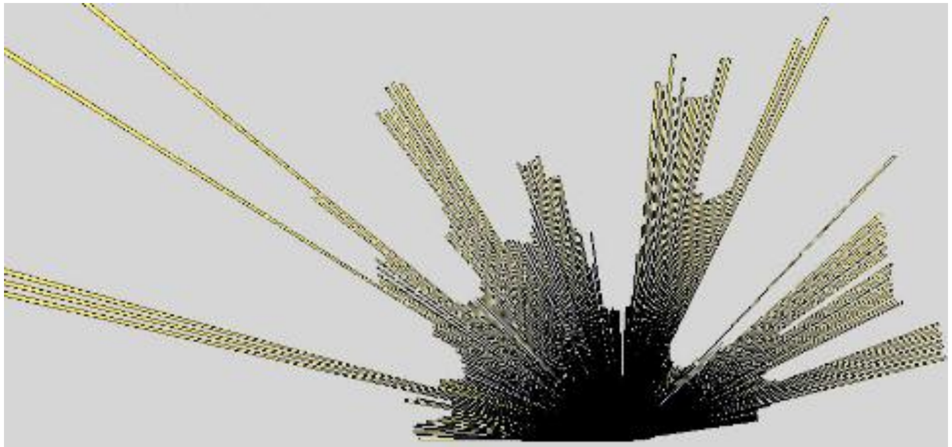
Room traverse by grid map from SONAR



Laser Range Finder Sensor Model

Lasers are definitely more accurate sensors

- 180 ranges over 180°
  (up to 360 in some models)
- 1 to 64 planes scanned
- 10-75 scans/second
- <1cm range resolution
- Max range up to 50-80 m
- Problems only with mirrors, glass, and matte bla



< 1000 €

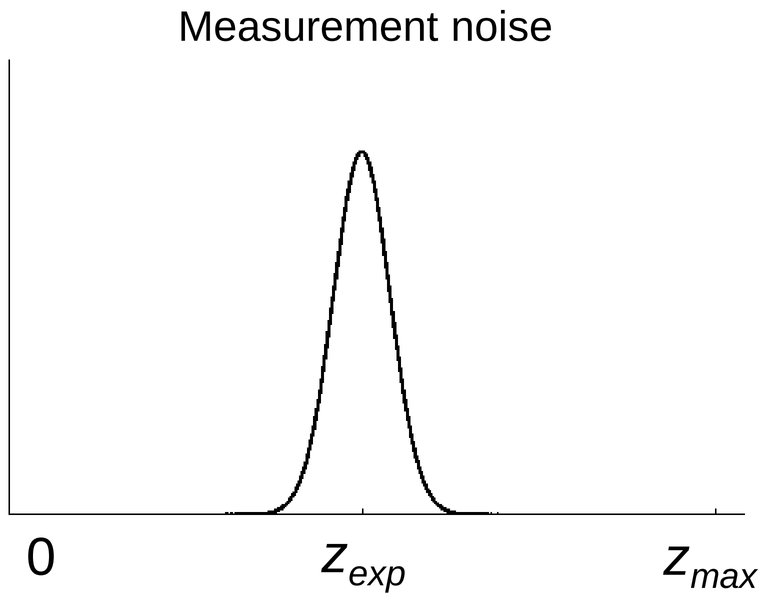
~ 6000 €

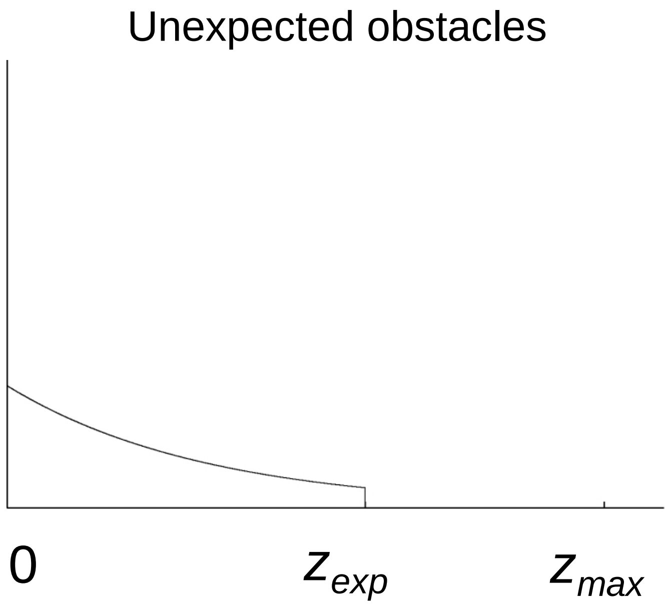
~ 40.000 €

> 80.000 €

Beam Based Sensor Model (I)

The laser range finder model describe each single measurement using



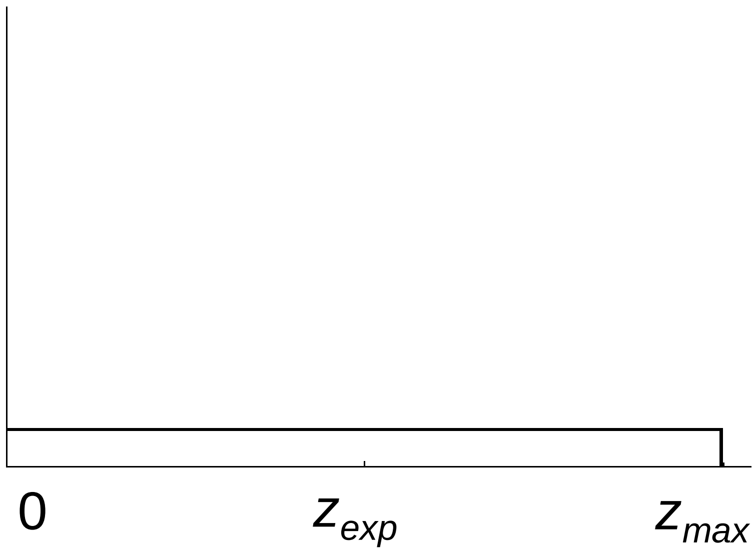


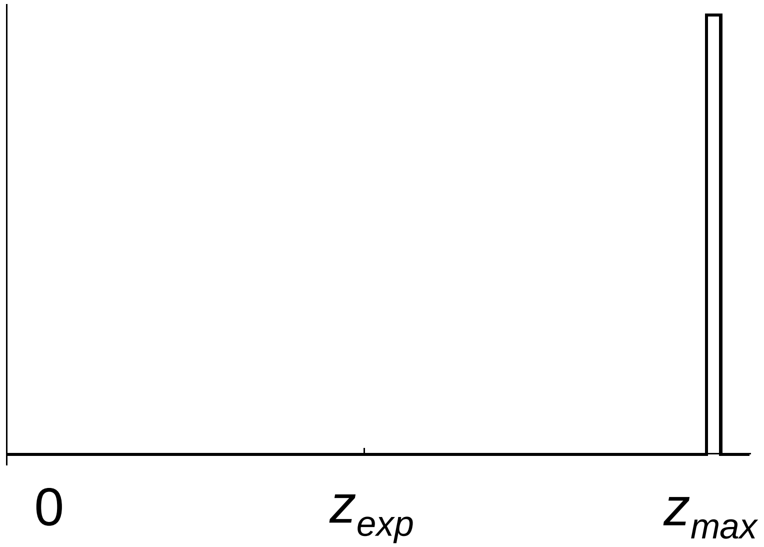
$$P_{hit}(z \mid x, m) = \eta \frac{1}{\sqrt{2\pi b}} e^{-\frac{1}{2}\frac{(z - z_{exp})^2}{b}}$$

$$P_{unexp}(z \mid x, m) = \begin{cases} \eta \lambda e^{-\lambda z} & z < z_{exp} \\ 0 & otherwise \end{cases}$$

Beam Based Sensor Model (II)

The laser range finder model describe each single measurement using


Random measurement

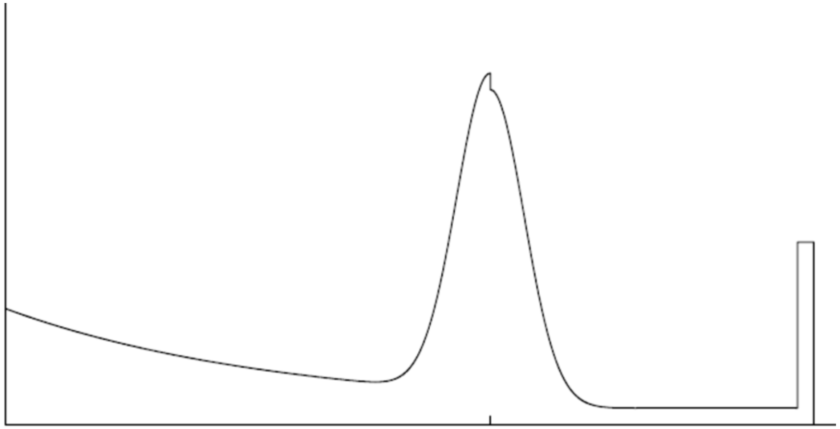

Max range

$$P_{rand}(z \mid x, m) = \eta \frac{1}{z_{\max}}$$

$$P_{\max}(z \mid x, m) = \eta \frac{1}{z_{small}}$$

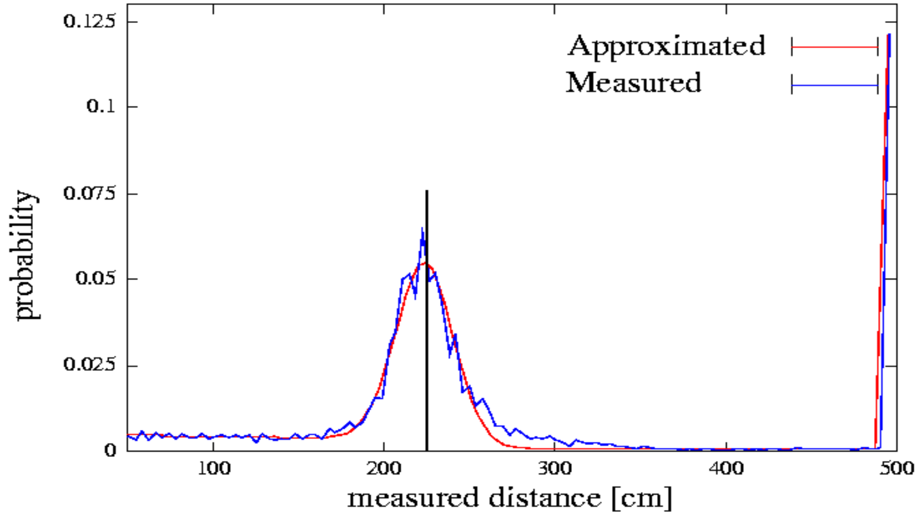
Beam Based Sensor Model (III)

The laser range finder model describe each single measurement using



$$P(z \mid x, m) = \begin{pmatrix} \alpha_{\text{hit}} \\ \alpha_{\text{unexp}} \\ \alpha_{\text{max}} \\ \alpha_{\text{rand}} \end{pmatrix}^T \cdot \begin{pmatrix} P_{\text{hit}}(z \mid x, m) \\ P_{\text{unexp}}(z \mid x, m) \\ P_{\text{max}}(z \mid x, m) \\ P_{\text{rand}}(z \mid x, m) \end{pmatrix}$$

Which, is practice, turns out to be quite accurate!



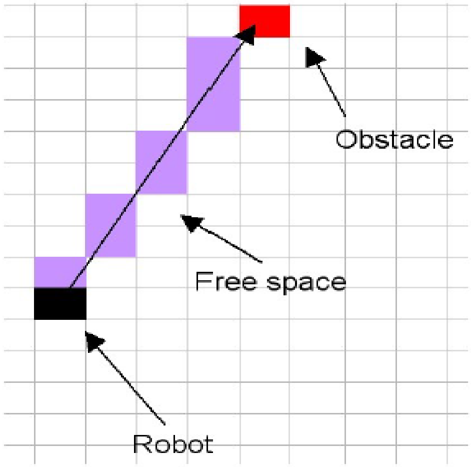
Occupancy Grid Cell Update

Let $occ(i,j)$ mean cell C_{ij} is occupied, then we have

- Probability: $p(occ(i,j))$ has range $[0,1]$
- Odds: $o(occ(i,j))$ has range $[0,+\infty)$

$$o(A) = \frac{P(A)}{P(\neg A)}$$

- Log odds: $\log o(occ(i,j))$ has range $(-\infty,+\infty)$
  - Each cell Cij holds the value $\log o\big(occ(i,j)\big)$
  - $Cij \ = \ 0$ corresponds to $p\big(occ(i,j)\big) = \ 0.5$



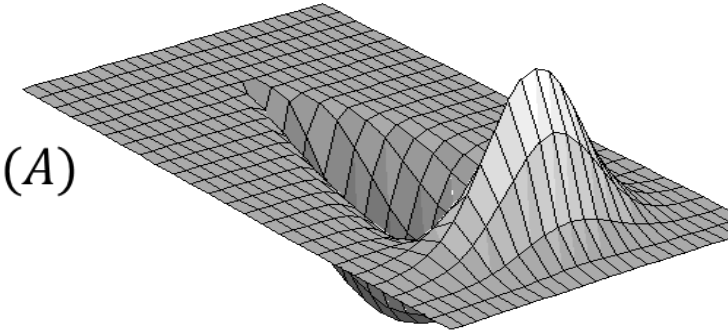
We will apply Bayes Law

- where *A* is *occ(i,j)*
- and *B* is an observation *r* = *D*

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

We can simplify this by using the log odds representation …

Occupancy by Log Odds



Lets consider Bayes law

- $o(A|B) = \frac{p(A|B)}{P(\neg A|B)} = \frac{p(B|A)P(A)}{P(B|\neg A)P(\neg A)} = \tau(B|A)o(A)$
- $\log o(A|B) = \log \tau(B|A) + \log o(A)$

To update the log odds of a cell at distance D

- $\log o(occ(i,j) \mid r = D) = \log \tau(\mathrm{r} = \mathrm{D} \mid \mathrm{occ(i,j)}) + \log o\left(occ(i,j)\right)$

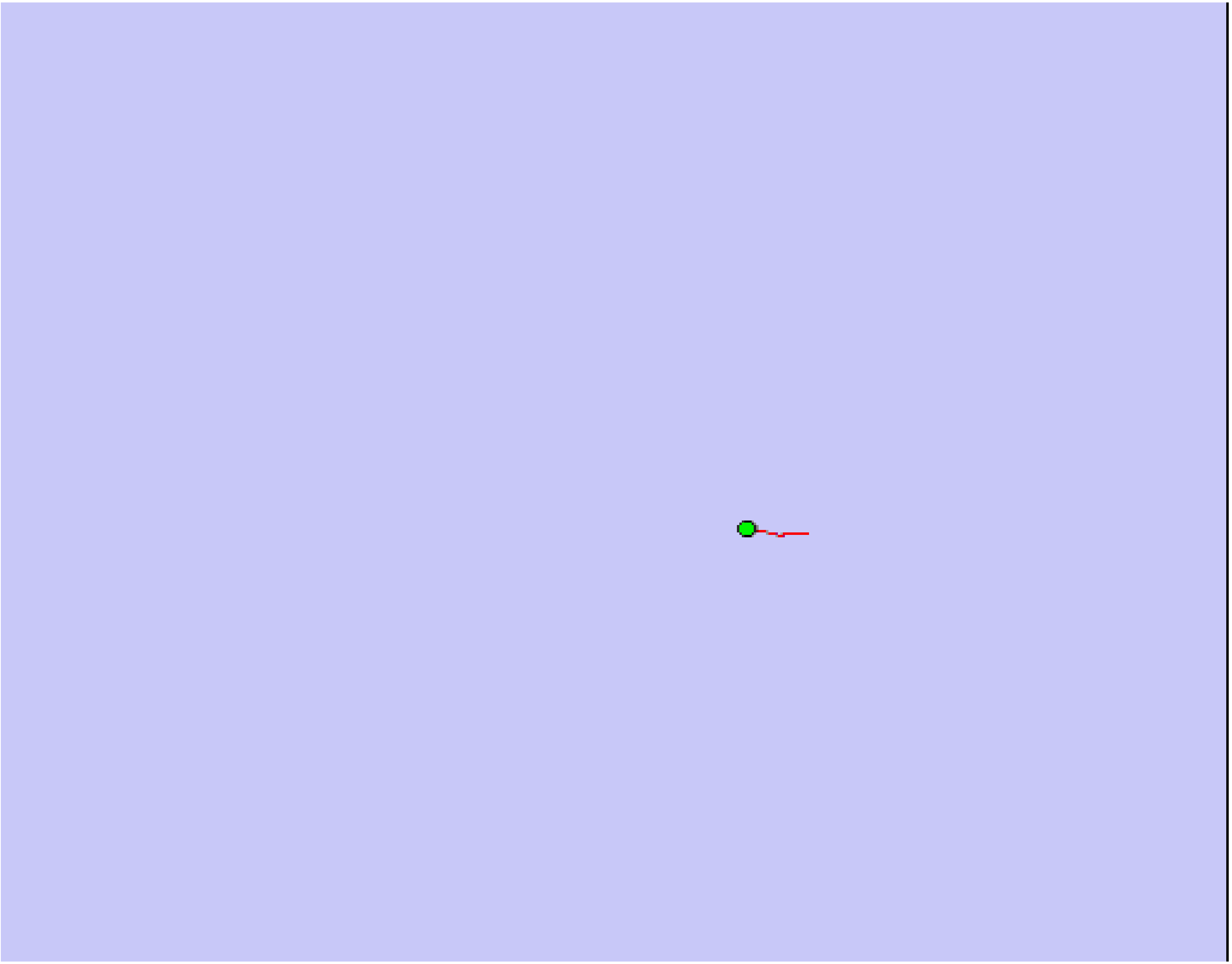
Assume cell C_{ij} holds $\log o\left(occ(i,j)\right)$

- Let be r the measurement from the sensor
- Let D be the distance of the cell
- For each cell C_{ij} accumulate evidence from each sensor reading

$$\tau(r = D|occ(i,j)) = \frac{p(r = D|occ(i,j))}{p(r = D|\neg occ(i,j))} \approx \frac{.06}{.005} = 12 \quad \rightarrow \quad log_2 \tau = 3.5$$

$$\tau(r > D|occ(i,j)) = \frac{p(r > D|occ(i,j))}{p(r > D|\neg occ(i,j))} \approx \frac{.45}{.90} = .5 \quad \rightarrow \quad log_2 \tau = -1$$

Mapping with Raw Odometry (with known poses)



Scan Matching

Maximize the likelihood of the *i-th* pose and map relative to the *(i-1)-th* pose and map.

$$\hat{x}_t = \arg\max_{x_t} \; p(z_t \mid x_t, \hat{m}^{[t-1]}) \cdot p(x_t \mid u_{t-1}, \hat{x}_{t-1})$$

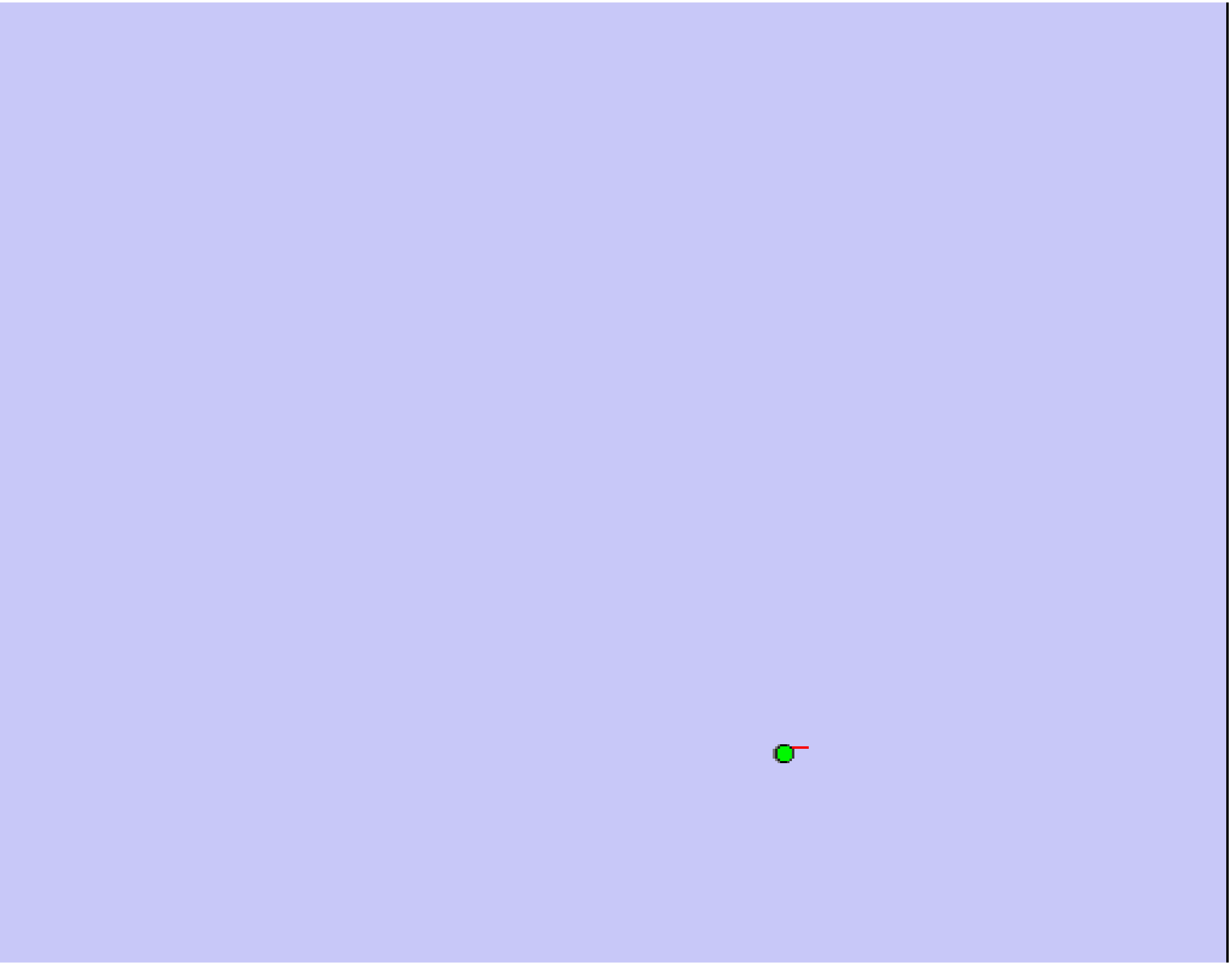
current measurement

robot motion

map constructed so far

Calculate the map $\hat{m}^{[t]}$ according to “mapping with known poses” based on the poses and observations.

Scan Matching Example



Techniques for Generating Consistent Maps

Several techniques have been studied to obtain a consistent estimate of the joint probability of pose and map

- Scan matching
- EKF SLAM / UKF SLAM
- Fast-SLAM (Particle filter based)
- Probabilistic mapping with a single map and a posterior about poses (Mapping + Localization)
- Graph-SLAM, SEIFs
- ...

We won’t see the all of them! ☺

SLAM: Simultaneous Localization and Mapping

Full SLAM:

$$p(x \quad m \mid z \quad u \quad)$$

Online Sl

$$dx_{t-1}$$

Two famous example of this!

Extended Kalman Filter (EKF) SLAM

- Solves online SLAM problem
- Uses a linearized Gaussian probability distribution model

FastSLAM

- Solves full SLAM problem
- Uses a sampled particle filter distribution model

Integrations typically done one at a time

Bayes Filters: Framework

Given:

- Stream of observations *z* and action data *u:*

$$d_t = \{u_1, z_1 \ldots, u_t, z_t\}$$

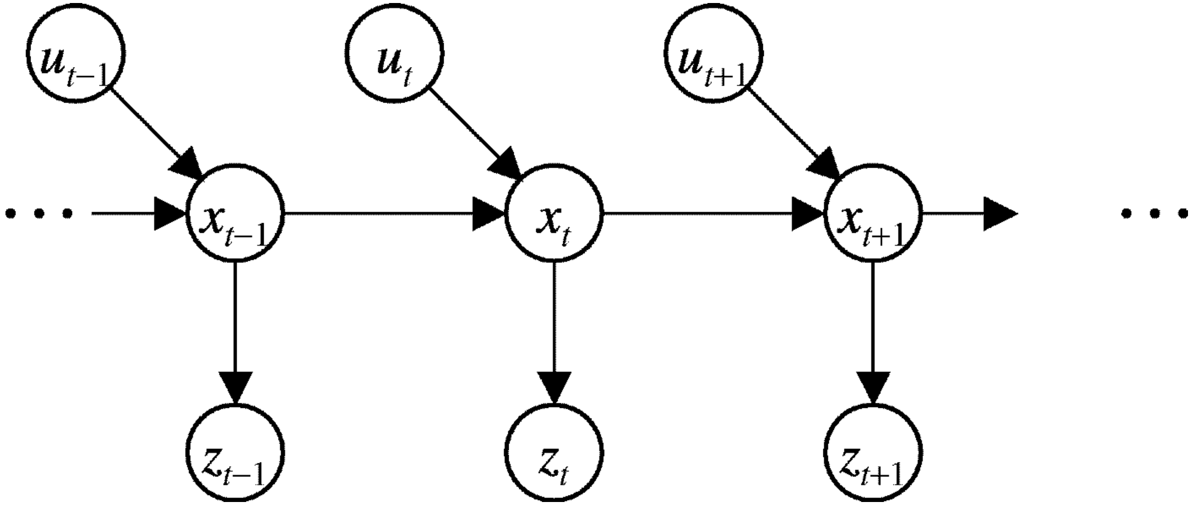
- Sensor model *P(z|x).*
- Action model *P(x|u,x')*.
- Prior probability of the system state *P(x).*

We want to compute:

- Estimate of the state *X* of a dynamical system.
- The posterior of the state is also called **Belief**:

$$Bel(x_t) = P(x_t \mid u_1, z_1 \ldots, u_t, z_t)$$

Markov Assumption


u_{t-1}
u_t
u_{t+1}
x_{t-1}
x_t
x_{t+1}
z_{t-1}
z_t
z_{t+1}
…
…

$$p(z_t \mid x_{0:t}, z_{1:t}, u_{1:t}) = p(z_t \mid x_t)$$

$$p(x_t \mid x_{1:t-1}, z_{1:t}, u_{1:t}) = p(x_t \mid x_{t-1}, u_t)$$

Underlying Assumptions

- Static world
- Independent noise
- Perfect model, no approximation errors

Bayes Filters

$$\boxed{Bel(x_t)} = P(x_t \mid u_1, z_1 \dots, u_t, z_t)$$

z = observation
u = action
x = state

Bayes $$= \eta \; P(z_t \mid x_t, u_1, z_1, \dots, u_t) \; P(x_t \mid u_1, z_1, \dots, u_t)$$

Markov $$= \eta \; P(z_t \mid x_t) \; P(x_t \mid u_1, z_1, \dots, u_t)$$

Total prob. $$= \eta \; P(z_t \mid x_t) \int P(x_t \mid u_1, z_1, \dots, u_t, x_{t-1}) \; P(x_{t-1} \mid u_1, z_1, \dots, u_t) \; dx_{t-1}$$

Markov $$= \eta \; P(z_t \mid x_t) \int P(x_t \mid u_t, x_{t-1}) \; P(x_{t-1} \mid u_1, z_1, \dots, u_t) \; dx_{t-1}$$

Markov $$= \eta \; P(z_t \mid x_t) \int P(x_t \mid u_t, x_{t-1}) \; P(x_{t-1} \mid u_1, z_1, \dots, z_{t-1}) \; dx_{t-1}$$

$$\boxed{= \eta \; P(z_t \mid x_t) \int P(x_t \mid u_t, x_{t-1}) \; Bel(x_{t-1}) \; dx_{t-1}}$$

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Bayes Filter: The Algorithm

$$Bel(x_t) = \eta \; P(z_t \mid x_t) \int P(x_t \mid u_t, x_{t-1}) \; Bel(x_{t-1}) \; dx_{t-1}$$

How to represent such belief?

```
Algorithm Bayes_filter( Bel(x), d ):
    $\eta = 0$
    If d is a perceptual data item z then
        For all x do
            $Bel'(x) = P(z \mid x) Bel(x)$
            $\eta = \eta + Bel'(x)$
        For all x do
            $Bel'(x) = \eta^{-1} Bel'(x)$
    Else if d is an action data item u then
        For all x do
            $Bel'(x) = \int P(x \mid u, x') \; Bel(x') \; dx'$
    Return Bel'(x)
```

(E)KF-SLAM

Map with N landmarks:(3+2N)-dimensional Gaussian

$$Bel(x_t, m_t) = \left\langle \begin{pmatrix} x \\ y \\ \theta \\ l_1 \\ l_2 \\ \vdots \\ l_N \end{pmatrix}, \begin{pmatrix} \sigma_x^2 & \sigma_{xy} & \sigma_{x\theta} & \sigma_{xl_1} & \sigma_{xl_2} & \cdots & \sigma_{xl_N} \\ \sigma_{xy} & \sigma_y^2 & \sigma_{y\theta} & \sigma_{yl_1} & \sigma_{yl_2} & \cdots & \sigma_{yl_N} \\ \sigma_{x\theta} & \sigma_{y\theta} & \sigma_\theta^2 & \sigma_{\theta l_1} & \sigma_{\theta l_2} & \cdots & \sigma_{\theta l_N} \\ \sigma_{xl_1} & \sigma_{yl_1} & \sigma_{\theta l_1} & \sigma_{l_1}^2 & \sigma_{l_1 l_2} & \cdots & \sigma_{l_1 l_N} \\ \sigma_{xl_2} & \sigma_{yl_2} & \sigma_{\theta l_2} & \sigma_{l_1 l_2} & \sigma_{l_2}^2 & \cdots & \sigma_{l_2 l_N} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ \sigma_{xl_N} & \sigma_{yl_N} & \sigma_{\theta l_N} & \sigma_{l_1 l_N} & \sigma_{l_2 l_N} & \cdots & \sigma_{l_N}^2 \end{pmatrix} \right\rangle$$

$$x_t = A_t x_{t-1} + B_t u_t + \varepsilon_t$$

$$p(x_t \mid u_t, x_{t-1}) = N\left(x_t ; A_t x_{t-1} + B_t u_t, R_t\right)$$

(E)KF-SLAM

Map with N landmarks:(3+2N)-dimensional Gaussian

$$Bel(x_t, m_t) = \left\langle \begin{pmatrix} x \\ y \\ \theta \\ l_1 \\ l_2 \\ \vdots \\ l_N \end{pmatrix}, \begin{pmatrix} \sigma_x^2 & \sigma_{xy} & \sigma_{x\theta} & \sigma_{xl_1} & \sigma_{xl_2} & \cdots & \sigma_{xl_N} \\ \sigma_{xy} & \sigma_y^2 & \sigma_{y\theta} & \sigma_{yl_1} & \sigma_{yl_2} & \cdots & \sigma_{yl_N} \\ \sigma_{x\theta} & \sigma_{y\theta} & \sigma_\theta^2 & \sigma_{\theta l_1} & \sigma_{\theta l_2} & \cdots & \sigma_{\theta l_N} \\ \sigma_{xl_1} & \sigma_{yl_1} & \sigma_{\theta l_1} & \sigma_{l_1}^2 & \sigma_{l_1 l_2} & \cdots & \sigma_{l_1 l_N} \\ \sigma_{xl_2} & \sigma_{yl_2} & \sigma_{\theta l_2} & \sigma_{l_1 l_2} & \sigma_{l_2}^2 & \cdots & \sigma_{l_2 l_N} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ \sigma_{xl_N} & \sigma_{yl_N} & \sigma_{\theta l_N} & \sigma_{l_1 l_N} & \sigma_{l_2 l_N} & \cdots & \sigma_{l_N}^2 \end{pmatrix} \right\rangle$$

$$\boxed{z_t = C_t x_t + \delta_t}$$

$$\boxed{p(z_t \mid x_t) = N(z_t; C_t x_t, Q_t)}$$

Bayes Filter: The Algorithm

$$Bel(x_t) = \eta\; P(z_t \mid x_t) \int P(x_t \mid u_t, x_{t-1})\; Bel(x_{t-1})\; dx_{t-1}$$

```
Algorithm Bayes_filter( Bel(x), d ):
    $\eta=0$
    If d is a perceptual data item z then
        For all x do
            $Bel'(x) = P(z \mid x) Bel(x)$
            $\eta = \eta + Bel'(x)$
        For all x do
            $Bel'(x) = \eta^{-1} Bel'(x)$
    Else if d is an action data item u then
        For all x do
            $Bel'(x) = \int P(x \mid u, x')\; Bel(x')\; dx'$
    Return Bel'(x)
```

correction

prediction

Kalman Filter Algorithm

Algorithm Kalman_filter(μ_{t-1}, Σ_{t-1}, u_t, z_t):

Prediction:

$$\bar{\mu}_t = A_t \mu_{t-1} + B_t u_t$$

$$\bar{\Sigma}_t = A_t \Sigma_{t-1} A_t^T + R_t$$

Correction:

$$K_t = \bar{\Sigma}_t C_t^T (C_t \bar{\Sigma}_t C_t^T + Q_t)^{-1}$$

$$\mu_t = \bar{\mu}_t + K_t (z_t - C_t \bar{\mu}_t)$$

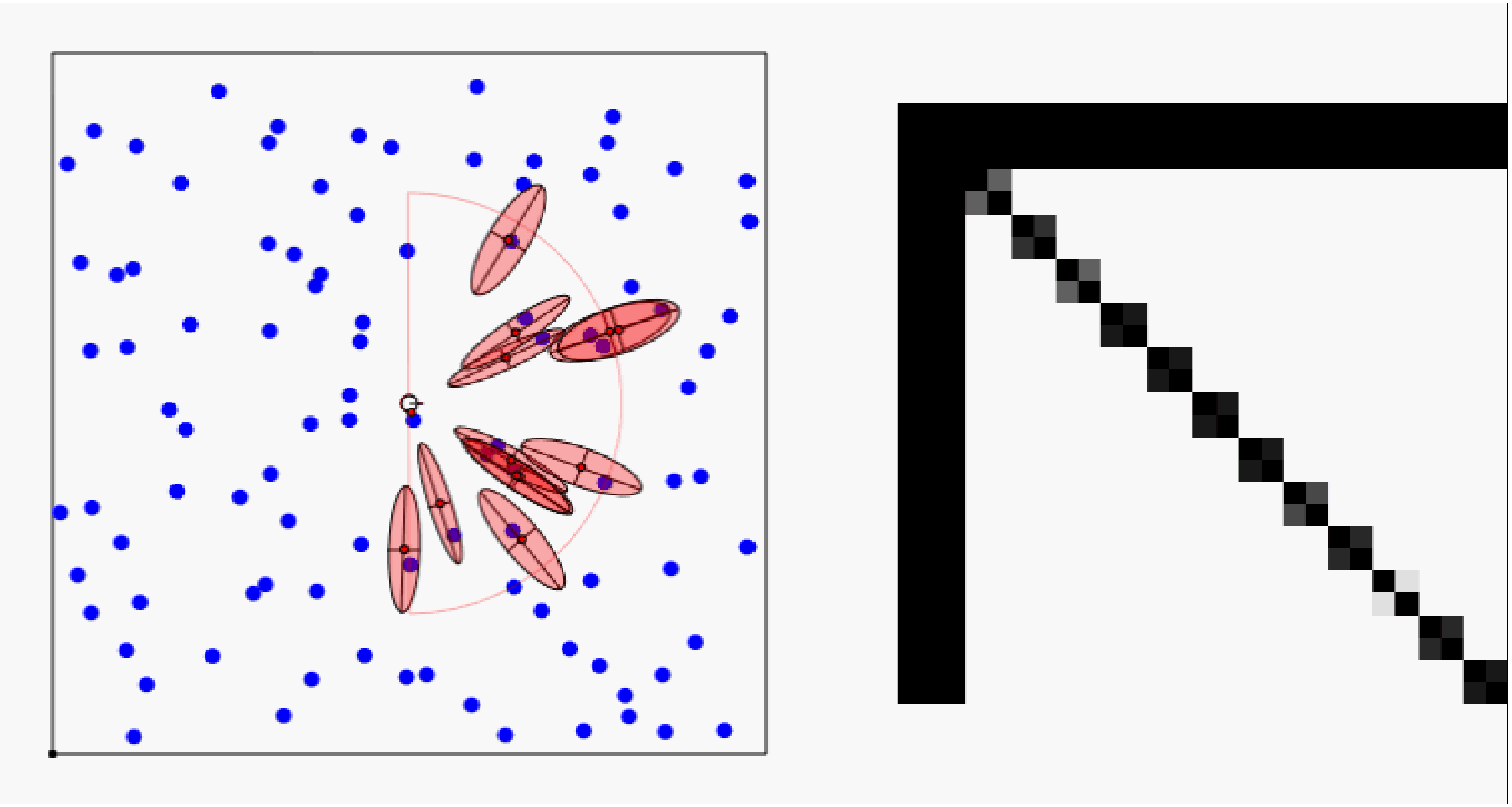
$$\Sigma_t = (I - K_t C_t) \bar{\Sigma}_t$$

Return μ_t, Σ_t `

$$Bel(x_t, m_t) = \left\langle \begin{pmatrix} x \\ y \\ \theta \\ l_1 \\ l_2 \\ \vdots \\ l_N \end{pmatrix}, \begin{pmatrix} \sigma_x^2 & \sigma_{xy} & \sigma_{x\theta} & \sigma_{xl_1} & \sigma_{xl_2} & \cdots & \sigma_{xl_N} \\ \sigma_{xy} & \sigma_y^2 & \sigma_{y\theta} & \sigma_{yl_1} & \sigma_{yl_2} & \cdots & \sigma_{yl_N} \\ \sigma_{x\theta} & \sigma_{y\theta} & \sigma_\theta^2 & \sigma_{\theta l_1} & \sigma_{\theta l_2} & \cdots & \sigma_{\theta l_N} \\ \sigma_{xl_1} & \sigma_{yl_1} & \sigma_{\theta l_1} & \sigma_{l_1}^2 & \sigma_{l_1 l_2} & \cdots & \sigma_{l_1 l_N} \\ \sigma_{xl_2} & \sigma_{yl_2} & \sigma_{\theta l_2} & \sigma_{l_1 l_2} & \sigma_{l_2}^2 & \cdots & \sigma_{l_2 l_N} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ \sigma_{xl_N} & \sigma_{yl_N} & \sigma_{\theta l_N} & \sigma_{l_1 l_N} & \sigma_{l_2 l_N} & \cdots & \sigma_{l_N}^2 \end{pmatrix} \right\rangle$$

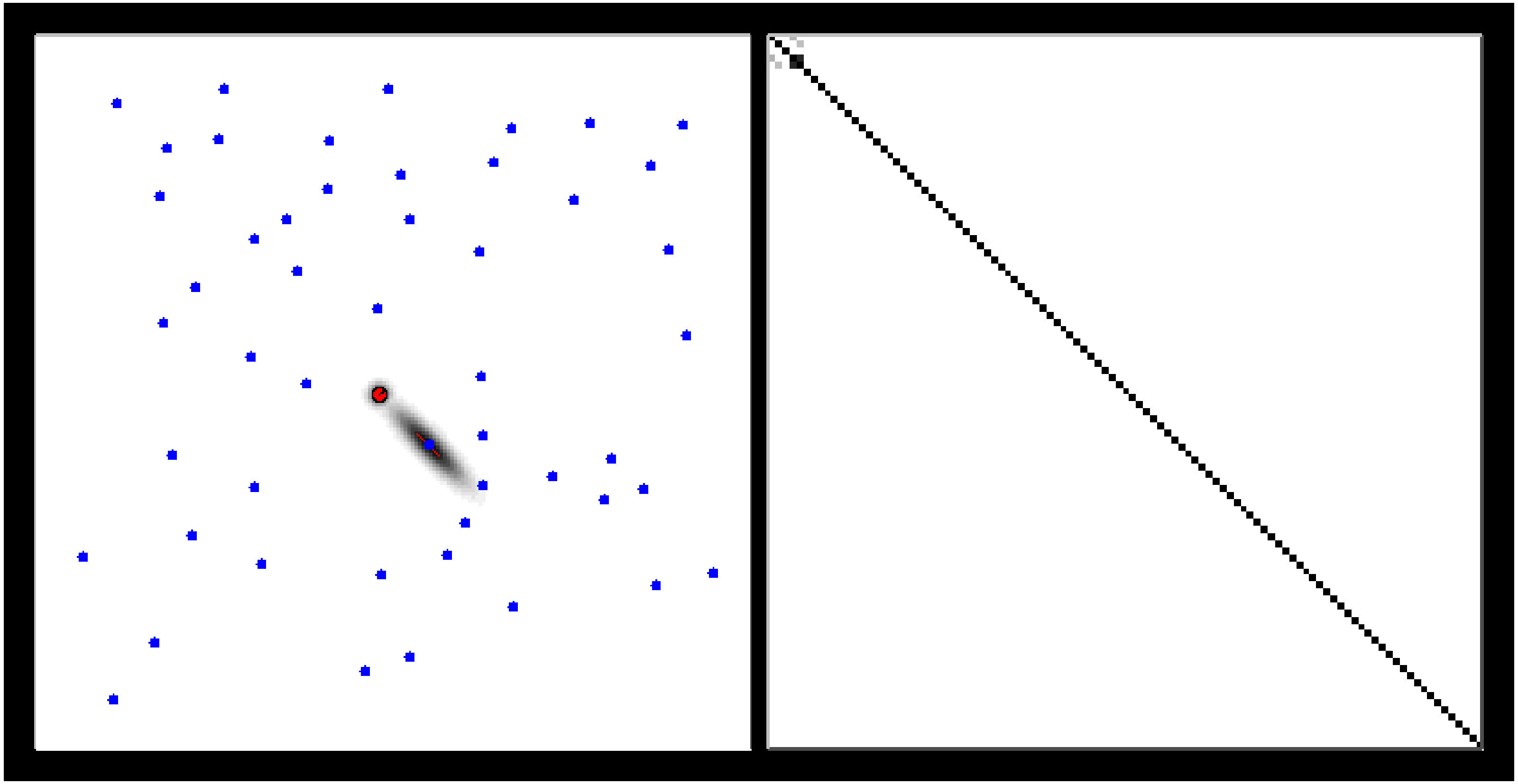
Classical Solution – The EKF

Approximate the SLAM posterior with a high-dimensional Gaussian



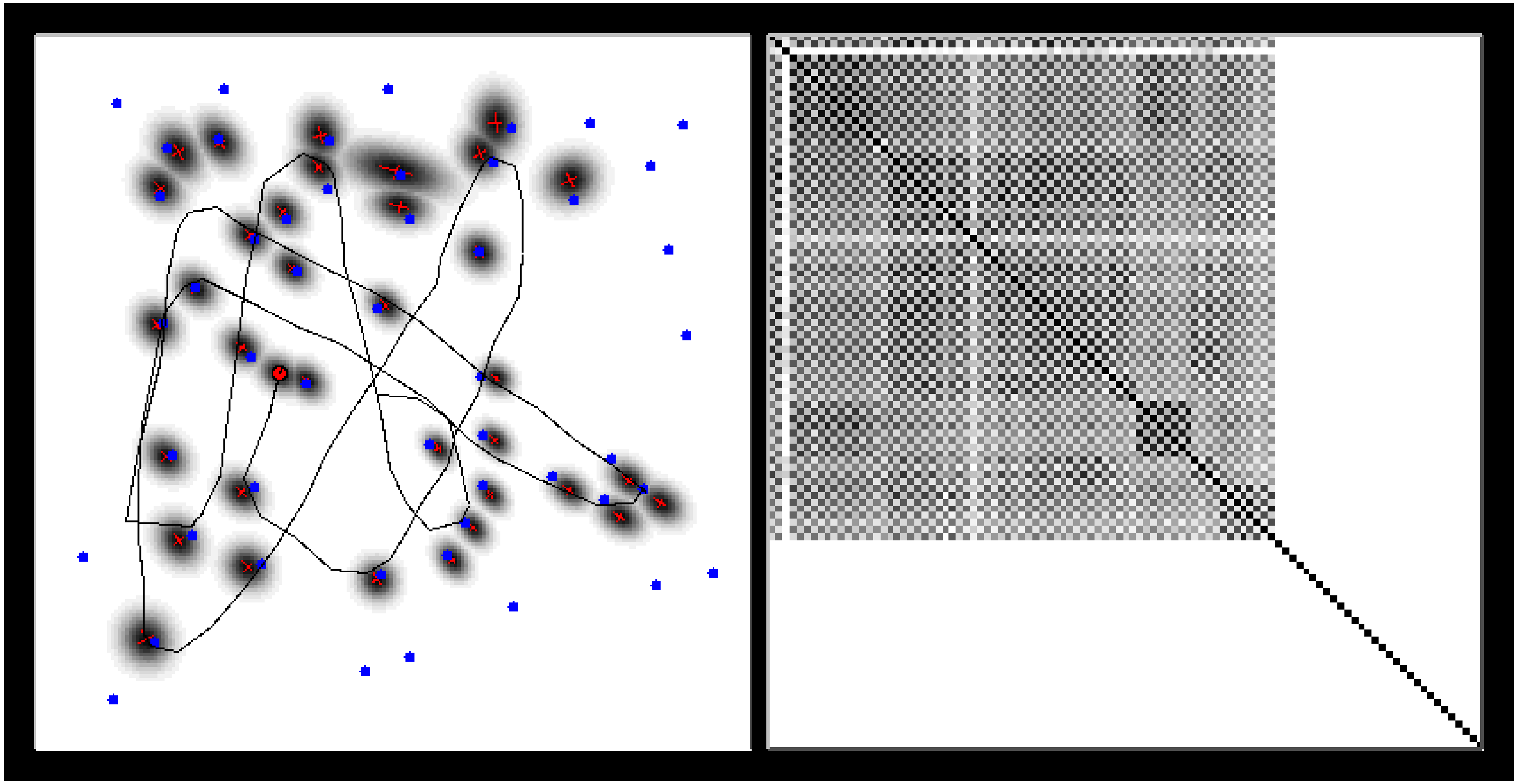
Blue path = true path **Red path** = estimated path **Black path** = odometry

EKF-SLAM



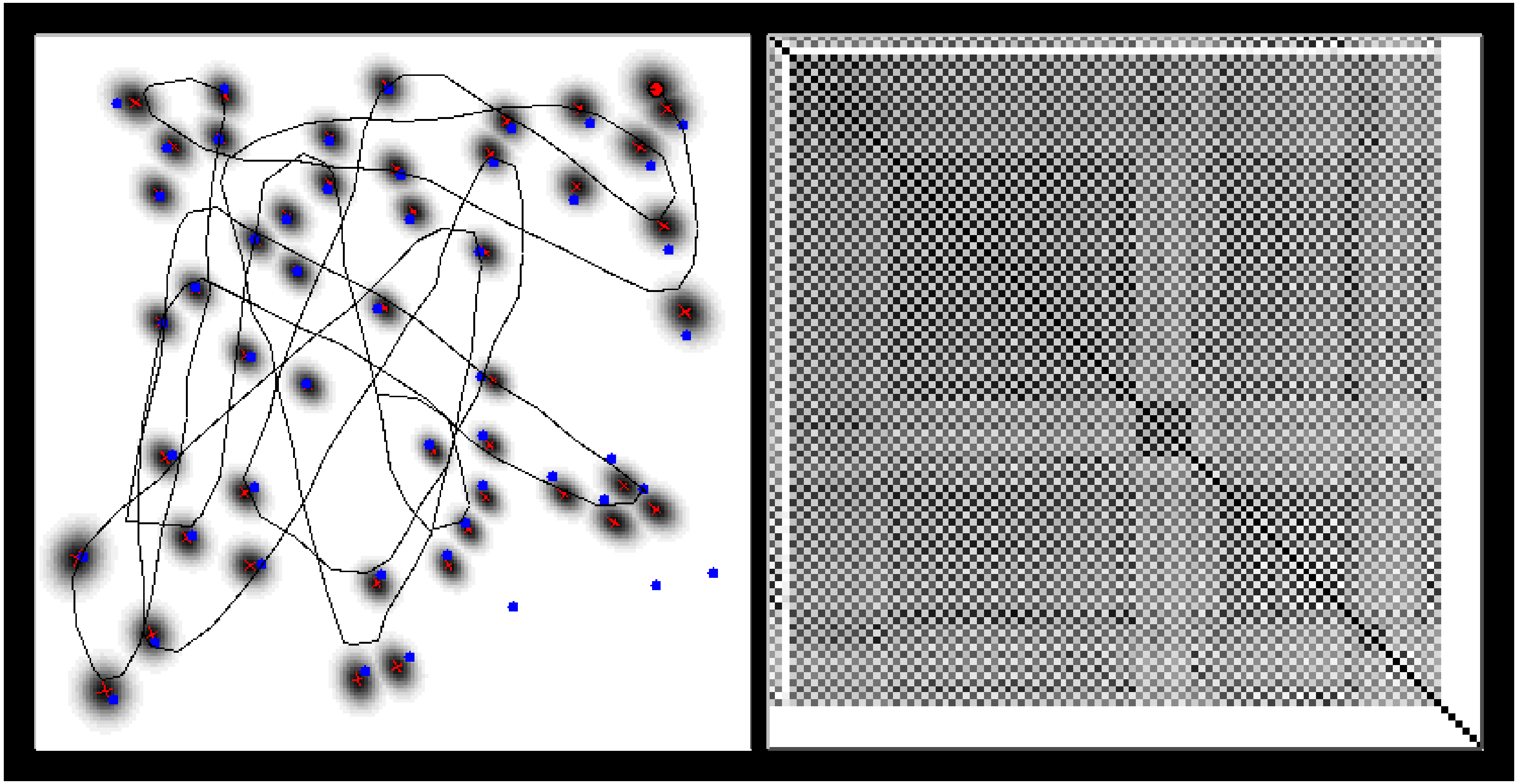
Map Correlation matrix

EKF-SLAM



Map Correlation matrix

EKF-SLAM



Map Correlation matrix

Properties of KF-SLAM (Linear Case)

Theorem:

[Dissanayake et al., 2001]

The determinant of any sub-matrix of the map covariance matrix decreases monotonically as successive observations are made.

Theorem:

In the limit the landmark estimates become fully correlated

Are we happy about this?

- Quadratic in the number of landmarks: $O(n^2)$
- Convergence results for the linear case.
- Can diverge if nonlinearities are large!
- Have been applied successfully in large-scale environments.
- Approximations reduce the computational complexity.

EKF Drawbacks

EKF-SLAM works pretty well but ...

- EKF-SLAM employs linearized models of nonlinear motion and observation models and so inherits many caveats.
- Computational effort is demand because computation grows quadratically with the number of landmarks.

Possible solutions

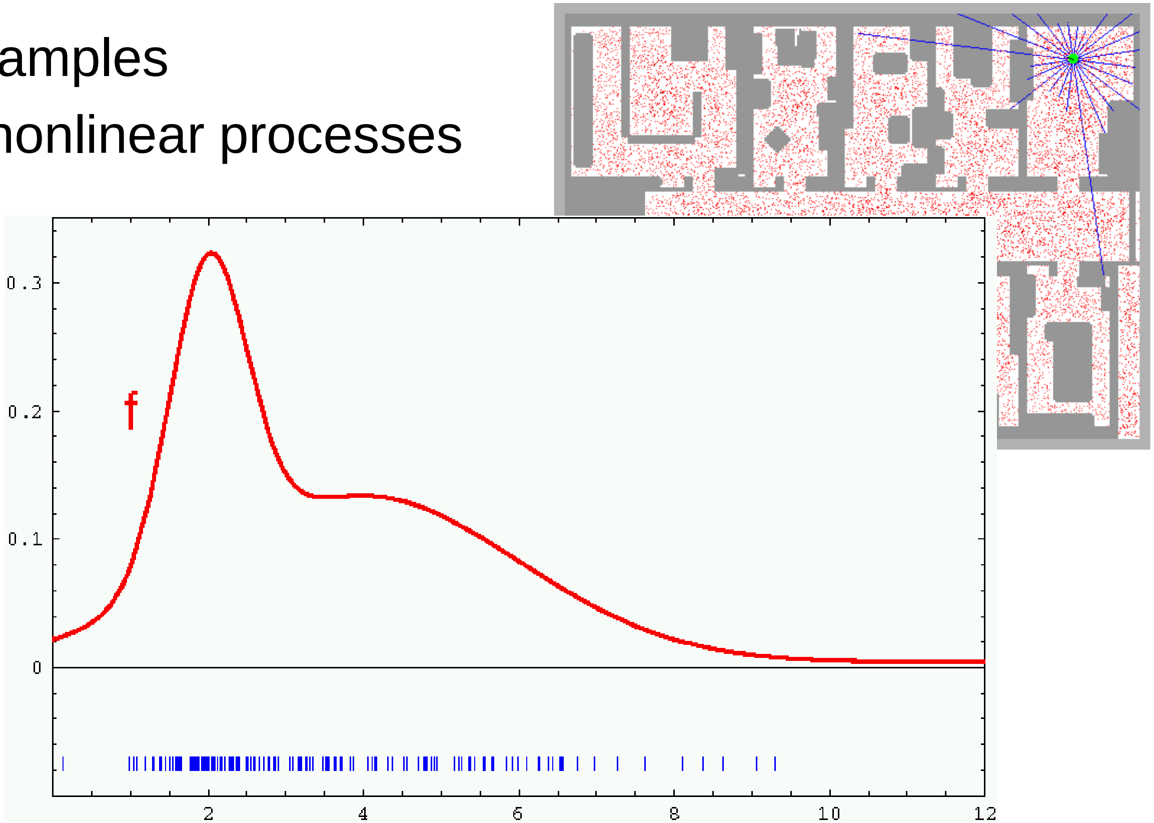
- Local submaps [Leonard & al 99, Bosse & al 02, Newman & al 03]
- Sparse links (correlations) [Lu & Milios 97, Guivant & Nebot 01]
- Sparse extended information filters [Frese et al. 01, Thrun et al. 02]
- Thin junction tree filters [Paskin 03]
- Rao-Blackwellisation (FastSLAM) [Murphy 99, Montemerlo et al. 02, Eliazar et al. 03, Haehnel et al. 03]
  - Represents nonlinear process and non-Gaussian uncertainty
  - Rao-Blackwellized method reduces computation

Particle Filters

Represent belief by random samples

Estimation of non-Gaussian, nonlinear processes

- Monte Carlo filter
- Survival of the fittest
- Condensation
- Bootstrap filter
- Particle filter
- …

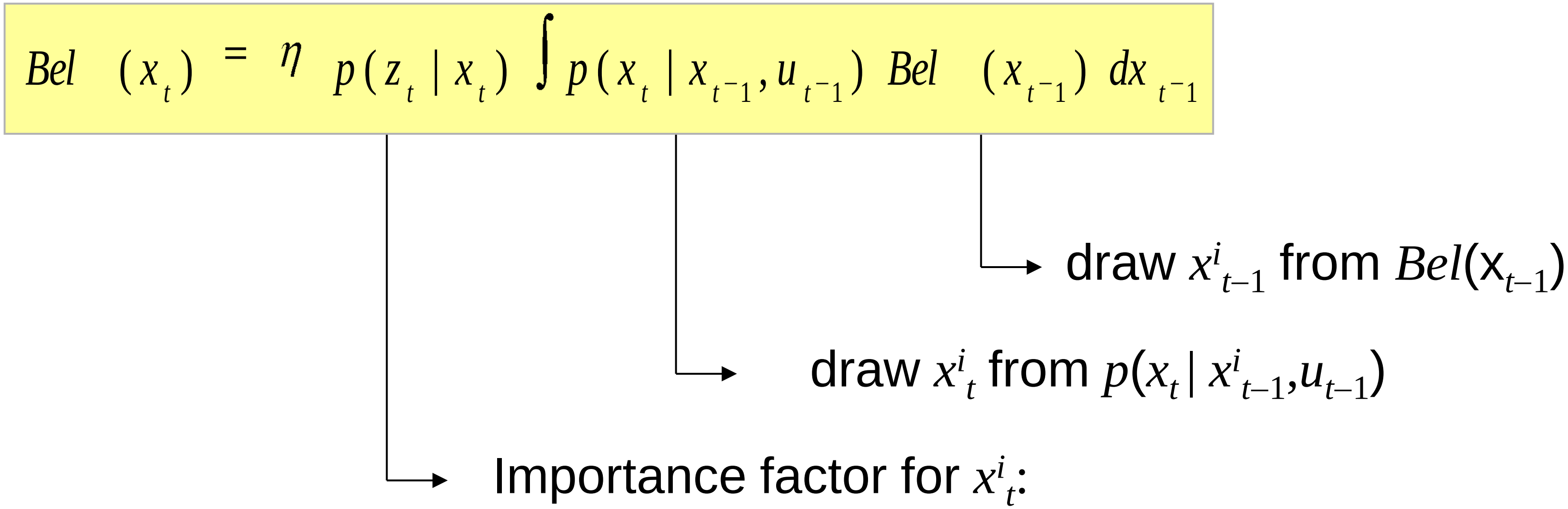


Filtering: [Rubin, 88], [Gordon et al., 93], [Kitagawa 96]

Computer vision: [Isard and Blake 96, 98]

Dynamic Bayesian Networks: [Kanazawa et al., 95]

Particle Filter Algorithm



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

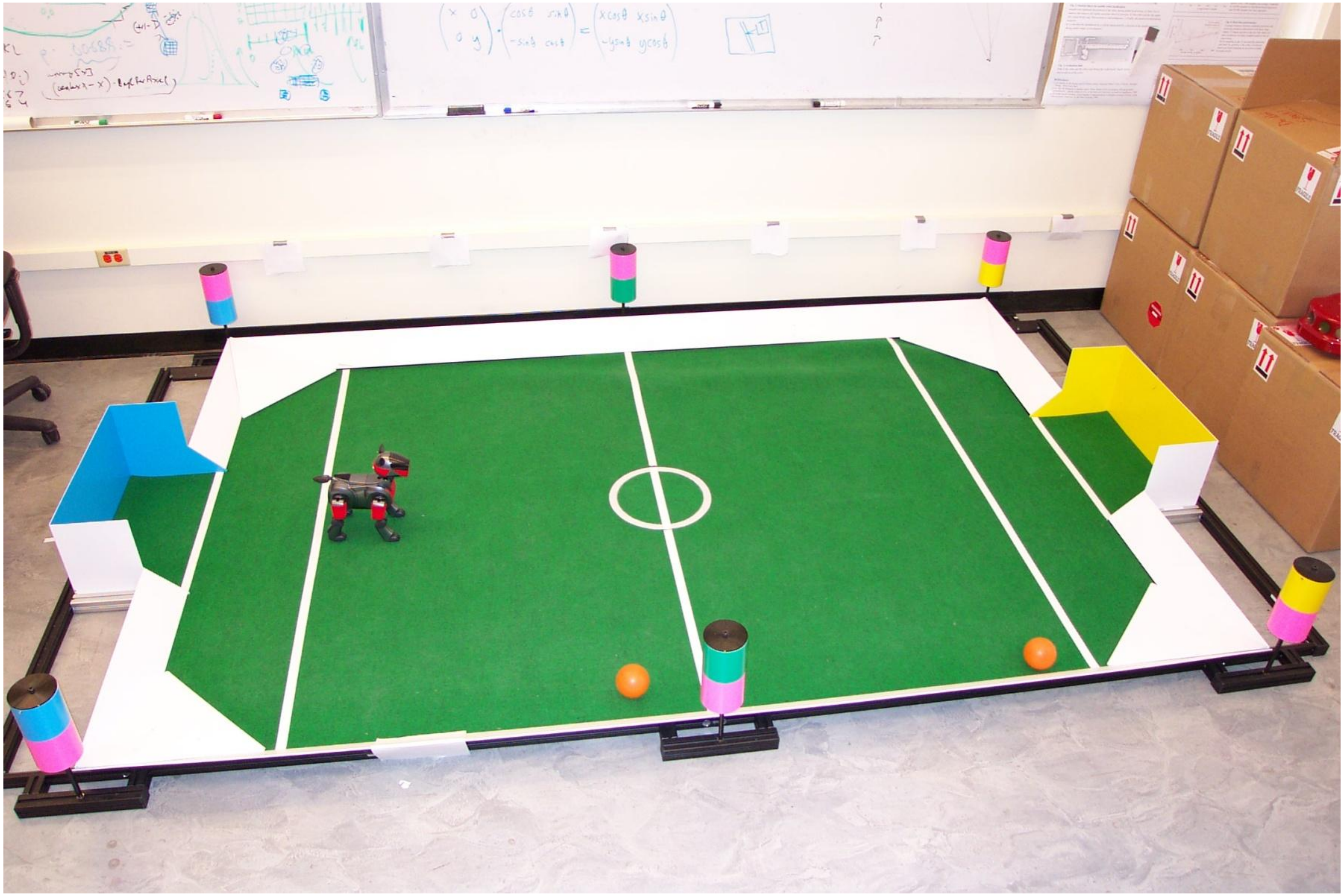
draw x^i_{t-1} from $Bel(x_{t-1})$

draw x^i_t from $p(x_t \mid x^i_{t-1}, u_{t-1})$

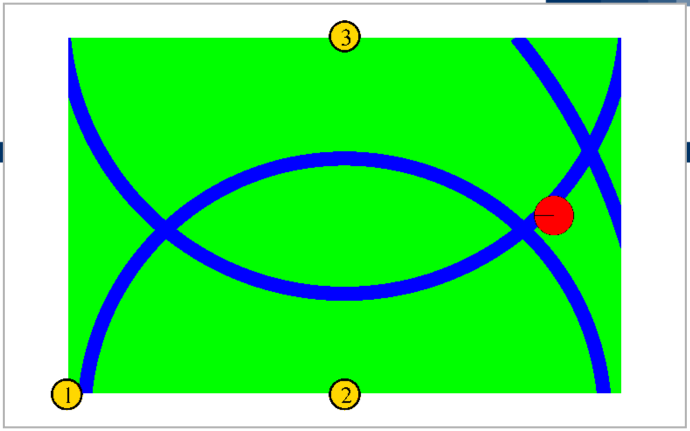
Importance factor for x^i_t:

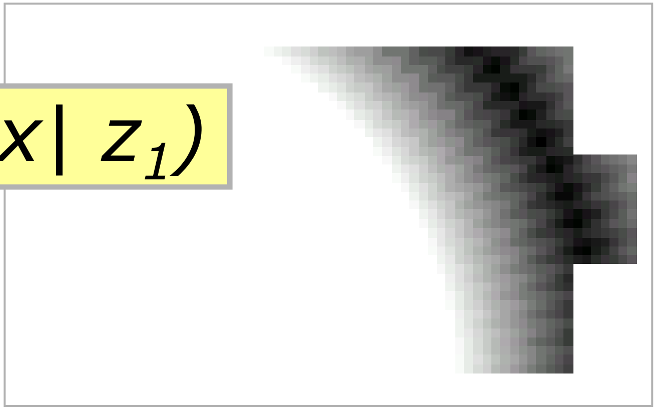
$$w_t^i = \frac{\text{target distribution}}{\text{proposal distribution}} = \frac{\eta\, p(z_t \mid x_t)\, p(x_t \mid x_{t-1}, u_{t-1})\, Bel(x_{t-1})}{p(x_t \mid x_{t-1}, u_{t-1})\, Bel(x_{t-1})} \propto p(z_t \mid x_t)$$

A Four Legged Example …

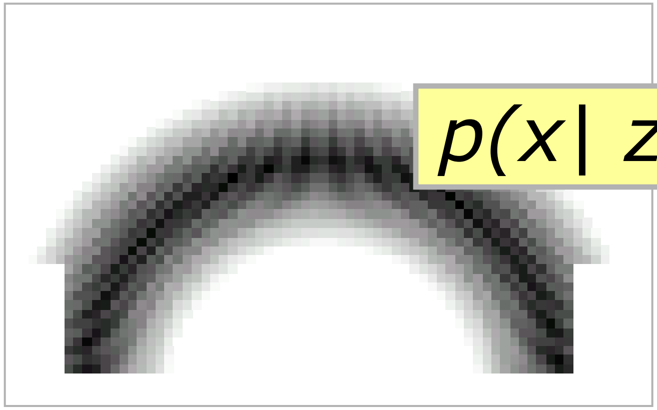


Involved Distributions

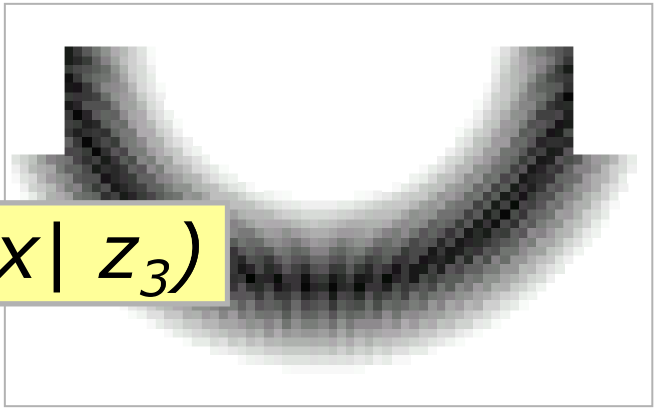




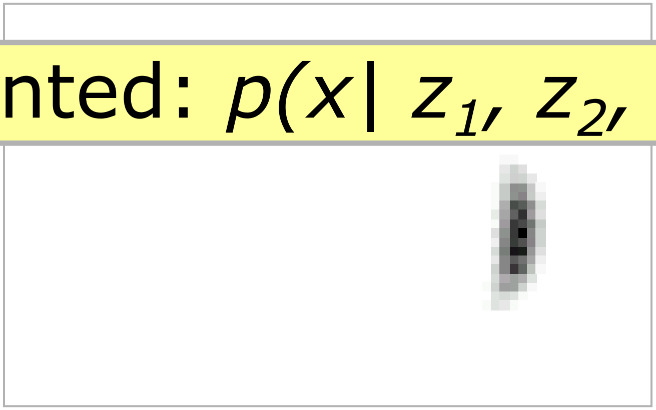
$p(x|\, z_1)$



$p(x|\, z_2)$



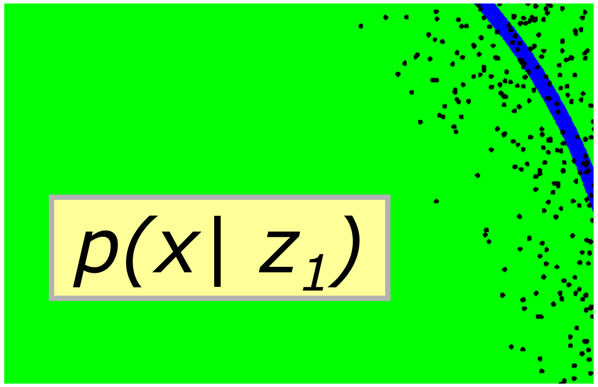
$p(x|\, z_3)$

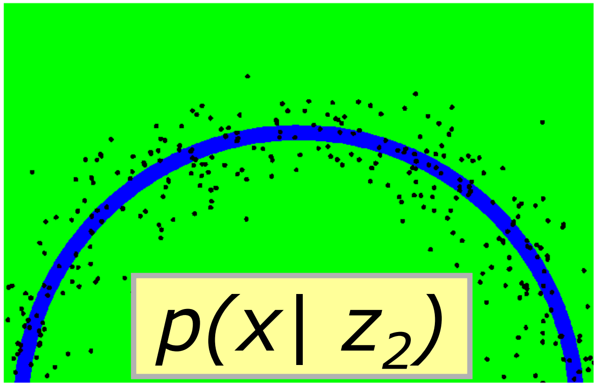


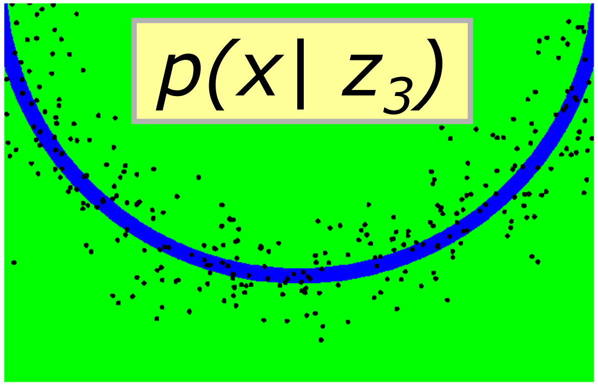
Wanted: $p(x|\, z_1, z_2, z_3)$

This is (somehow) easy!

Draw samples from $p(x|z_i)$ using the detection parameters and some noise





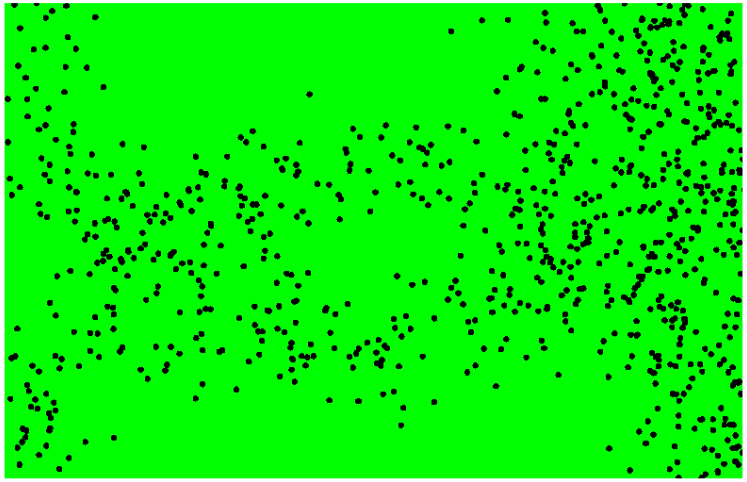


$$\text{Target distribution } f: p(x \mid z_1, z_2, \dots, z_n) = \frac{\prod_k p(z_k \mid x) \quad p(x)}{p(z_1, z_2, \dots, z_n)}$$

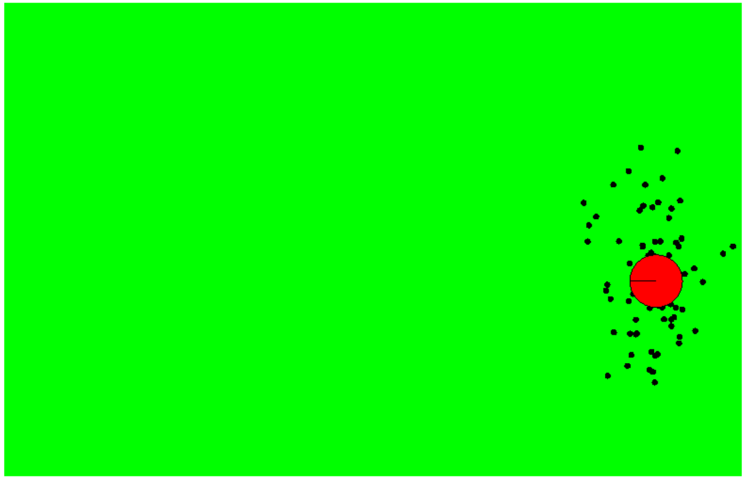
$$\text{Sampling distribution } g: p(x \mid z_l) = \frac{p(z_l \mid x)\, p(x)}{p(z_l)}$$

$$\text{Importance weights } w: \frac{f}{g} = \frac{p(x \mid z_1, z_2, \dots, z_n)}{p(x \mid z_l)} = \frac{p(z_l) \prod_{k \neq l} p(z_k \mid x)}{p(z_1, z_2, \dots, z_n)}$$

Importance Sampling with Resampling

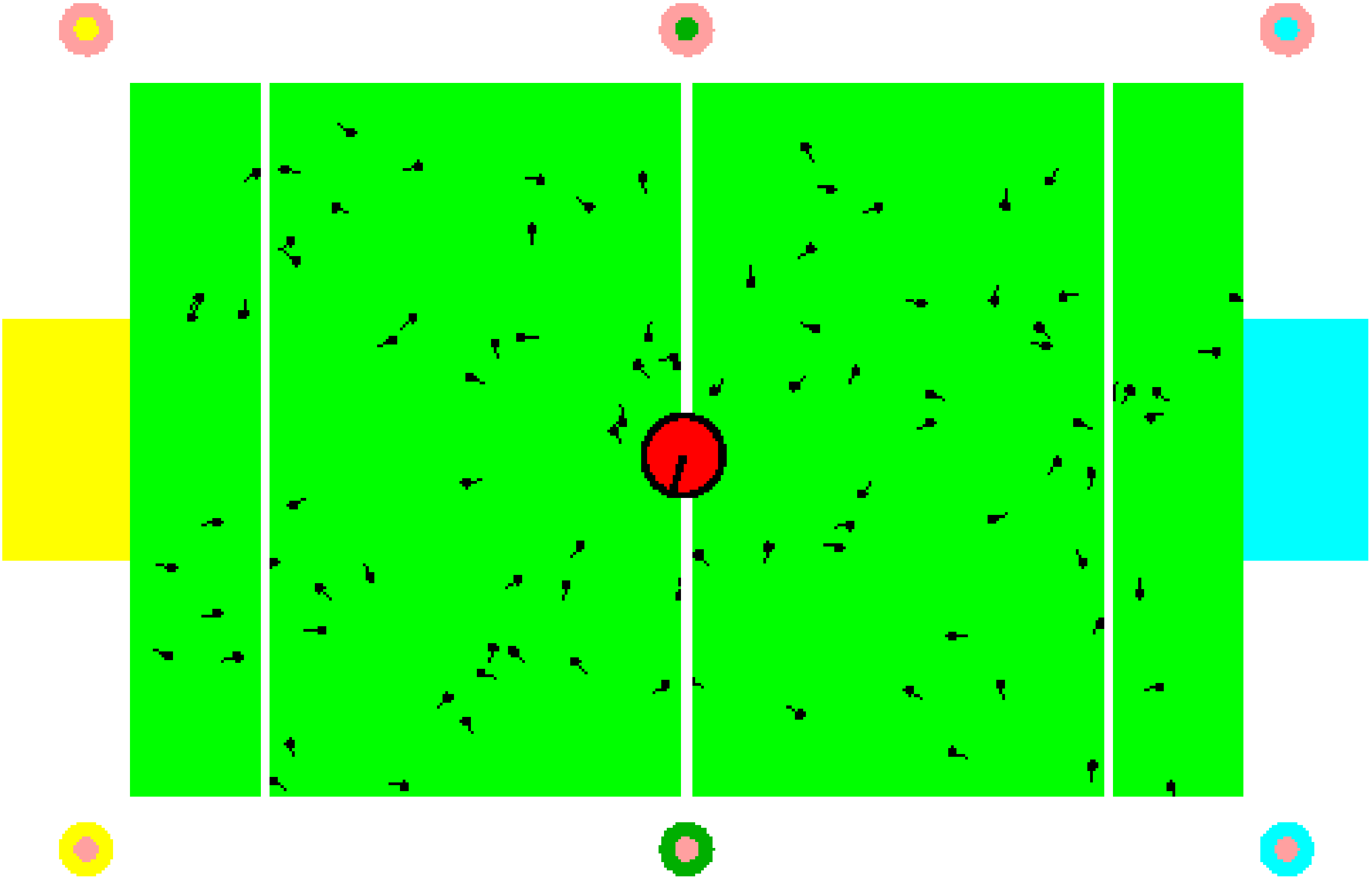


Weighted samples



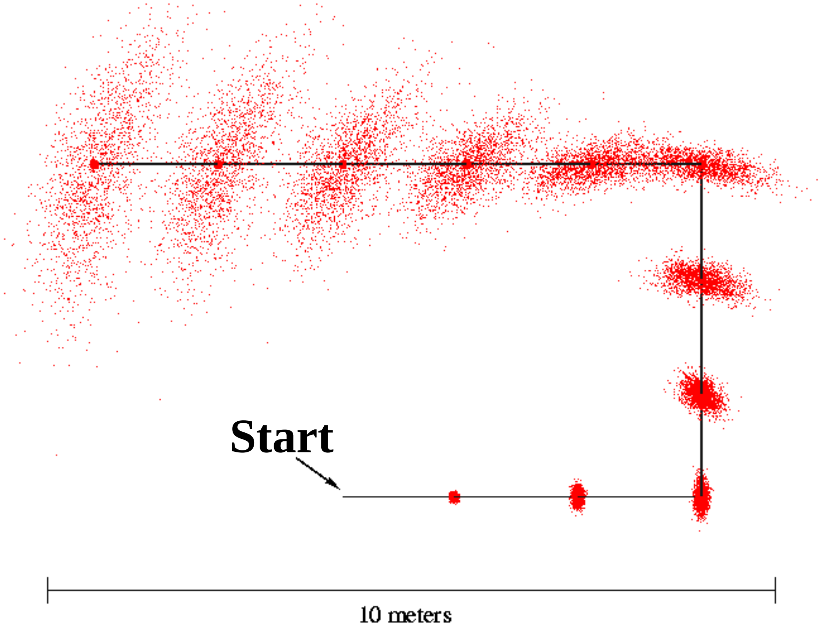
After resampling

Localization for AIBO robots

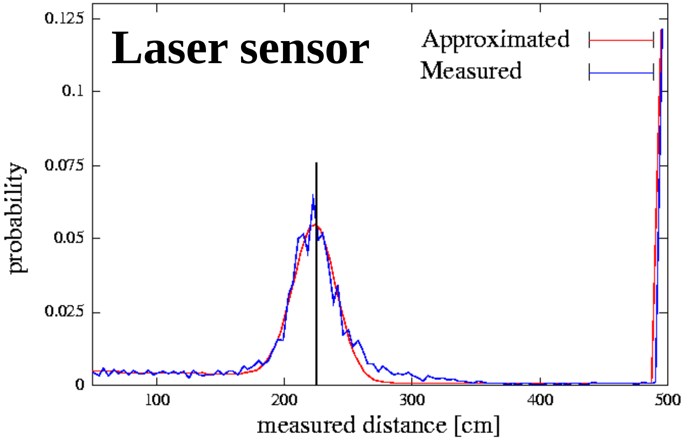


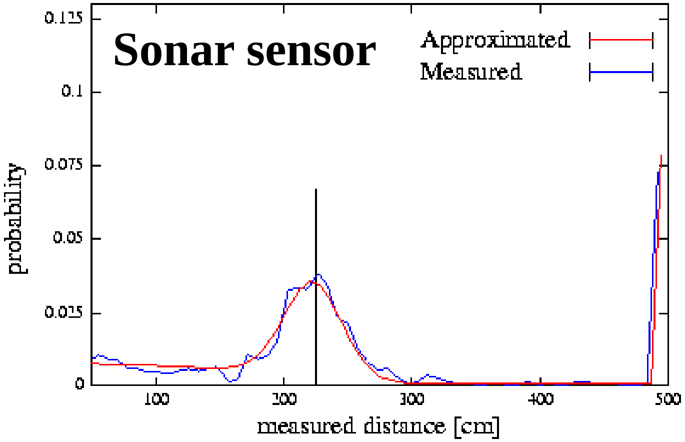
Monte Carlo Localization with Laser

Stochastic motion model

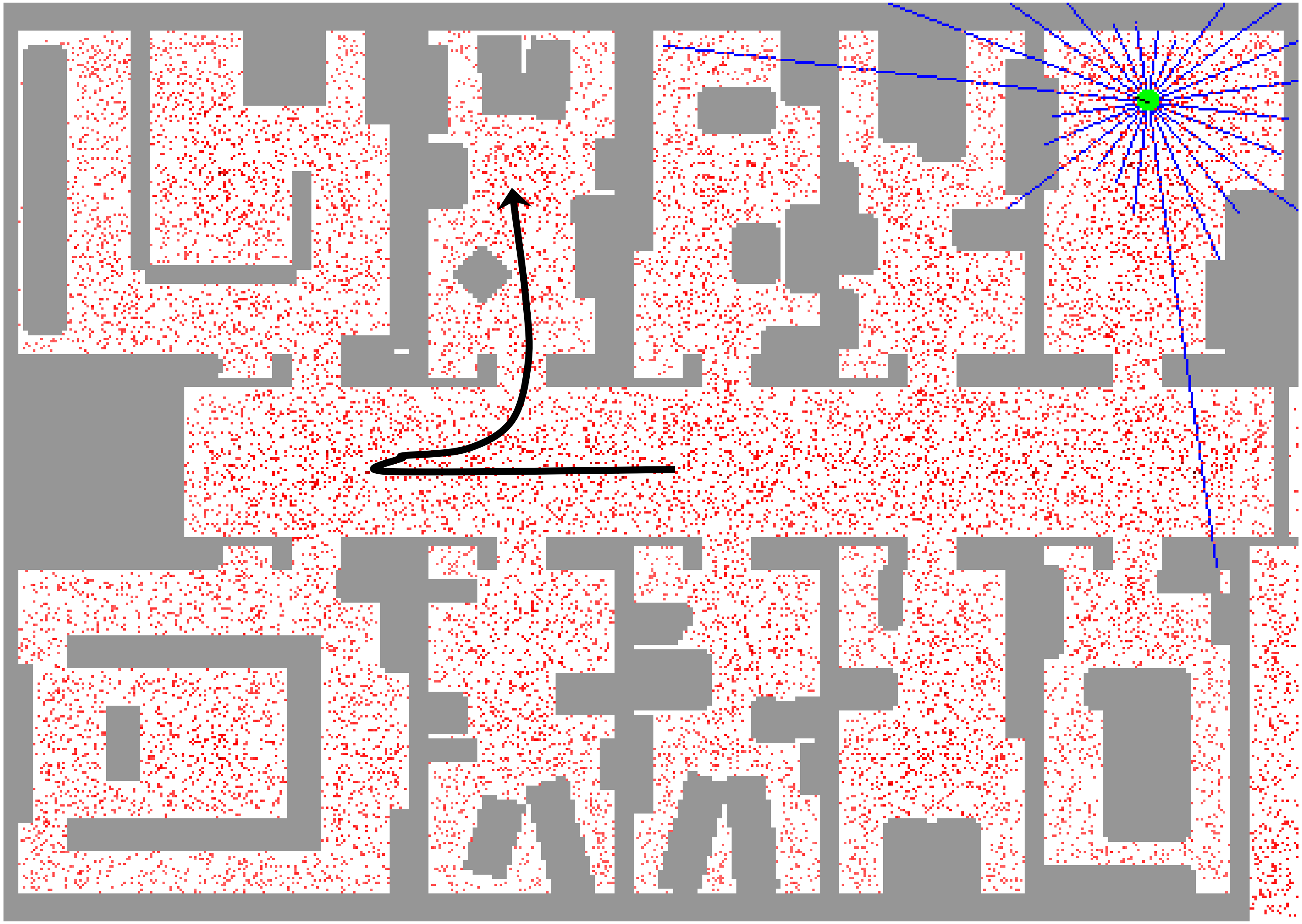


Proximity sensor model





Sample-based Localization (sonar)



The FastSLAM Idea (Full SLAM)

In the general case we have

$$p(x_t, m \mid z_t) \neq P(x_t \mid z_t) P(m \mid z_t)$$

However if we consider the full trajectory X_t rather than the single pose x_t.

$$p(X_t, m \mid z_t) = P(X_t \mid z_t) P(m \mid X_t, z_t)$$

In FastSLAM, the trajectory X_t is represented by particles X_t(i) while the map is represented by a factorization called Rao-Blackwellized Filter

$$P(m \mid X_t^{(i)}, z_t) = \prod_j^M P(m_j \mid X_t^{(i)}, z_t)$$

- $P(X_t \mid z_t)$ through particles
- $P(m \mid X_t, z_t)$ using an EKF

FastSLAM Formulation

Decouple map of features from pose ...

- Each particle represents a robot trajectory
- Feature measurements are correlated thought the robot trajectory
- If the robot trajectory is known all of the features would be uncorrelated
- Treat each pose particle as if it is the true trajectory, processing all of the feature measurements independently

poses map observations & movements

$$p(\overset{\text{poses}}{x_{1:t}}, \overset{\text{map}}{l_{1:m}} \mid z_{1:t}, \overset{\text{observations \& movements}}{u_{0:t-1}}) = \underbrace{p(x_{1:t} \mid z_{1:t}, u_{0:t-1})}_{\text{Robot path posterior}} \cdot \underbrace{p(l_{1:m} \mid x_{1:t}, z_{1:t})}_{\text{Landmark positions}}$$

SLAM posterior

Robot path posterior

Landmark positions

Factored Posterior: Rao-Blackwellization

$$\begin{aligned} p(x_{1:t}, l_{1:m} \mid z_{1:t}, u_{0:t-1}) \\ &= p(x_{1:t} \mid z_{1:t}, u_{0:t-1}) \cdot p(l_{1:m} \mid x_{1:t}, z_{1:t}) \\ &= p(x_{1:t} \mid z_{1:t}, u_{0:t-1}) \cdot \prod_{i=1}^{M} p(l_i \mid x_{1:t}, z_{1:t}) \end{aligned}$$

Robot path posterior
(localization problem)

Conditionally independent
landmark positions

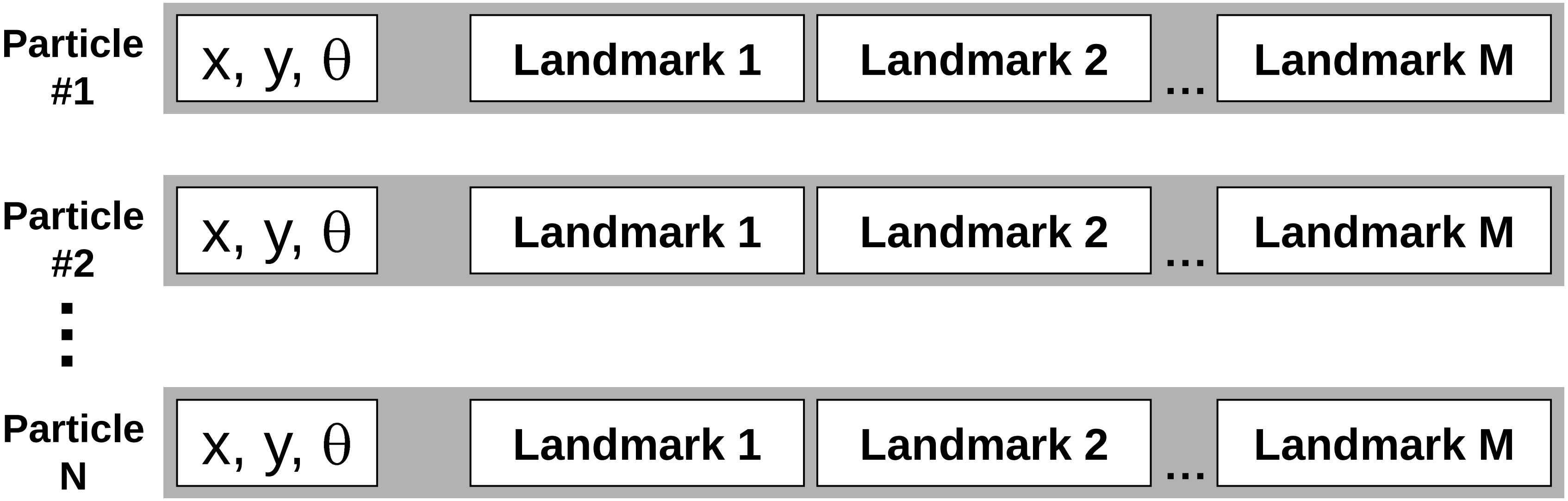
Dimension of state space is drastically reduced by factorization making particle filtering possible

$$p(x_{1:t}, l_{1:m} \mid z_{1:t}, u_{0:t-1}) =$$

$$p(x_{1:t} \mid z_{1:t}, u_{0:t-1}) \cdot \prod_{i=1}^{M} p(l_i \mid x_{1:t}, z_{1:t})$$

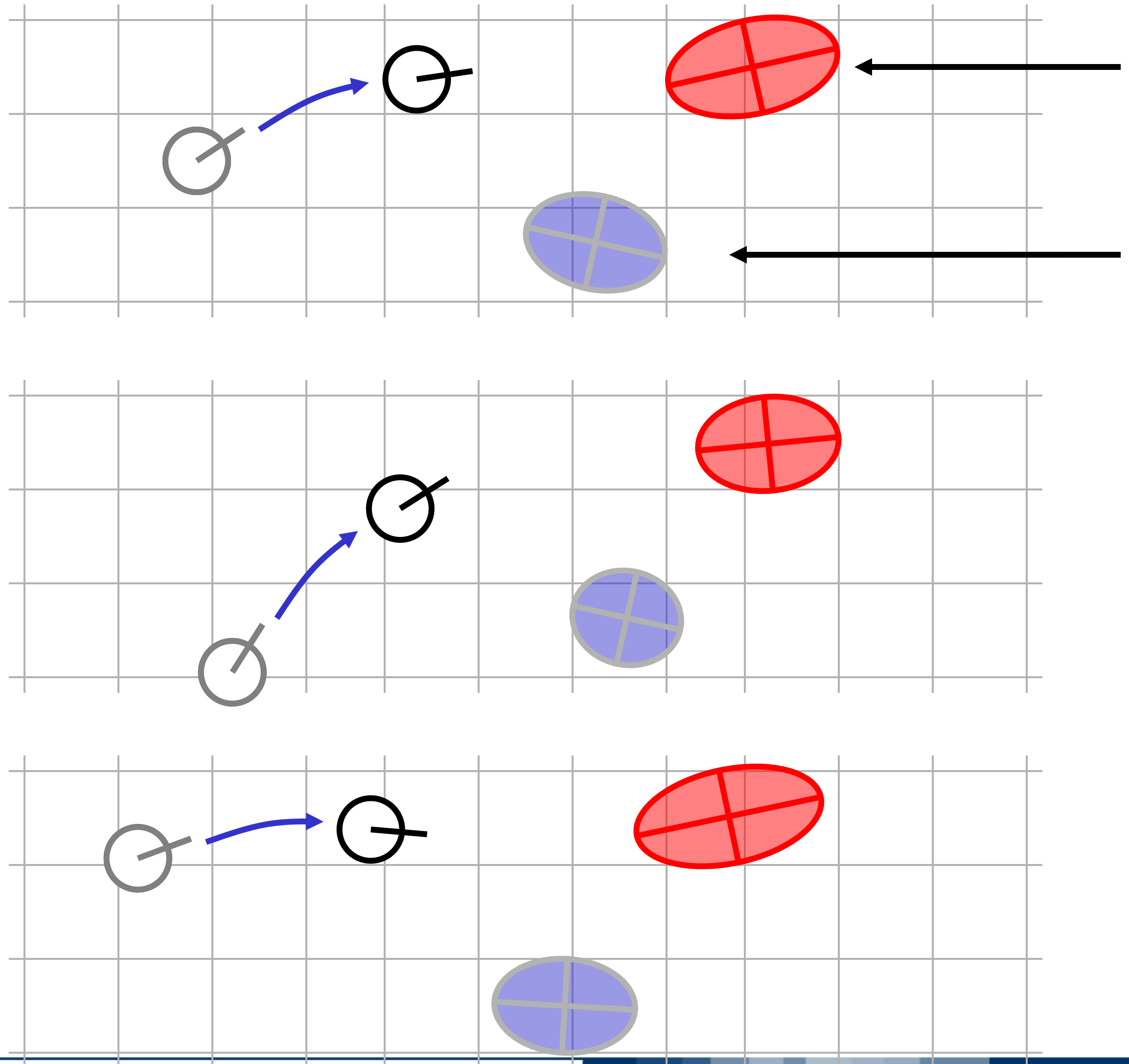
FastSLAM in Practice

- Rao-Blackwellized particle filtering based on landmarks [Montemerlo et al., 2002]
- Each landmark is represented by a 2x2 Extended Kalman Filter (EKF)
- Each particle therefore has to maintain M EKFs



Particle #1	x, y, θ	**Landmark 1**	**Landmark 2**	…	**Landmark M**
Particle #2	x, y, θ	**Landmark 1**	**Landmark 2**	…	**Landmark M**
⋮					
Particle N	x, y, θ	**Landmark 1**	**Landmark 2**	…	**Landmark M**

FastSLAM – Action Update



Particle #1

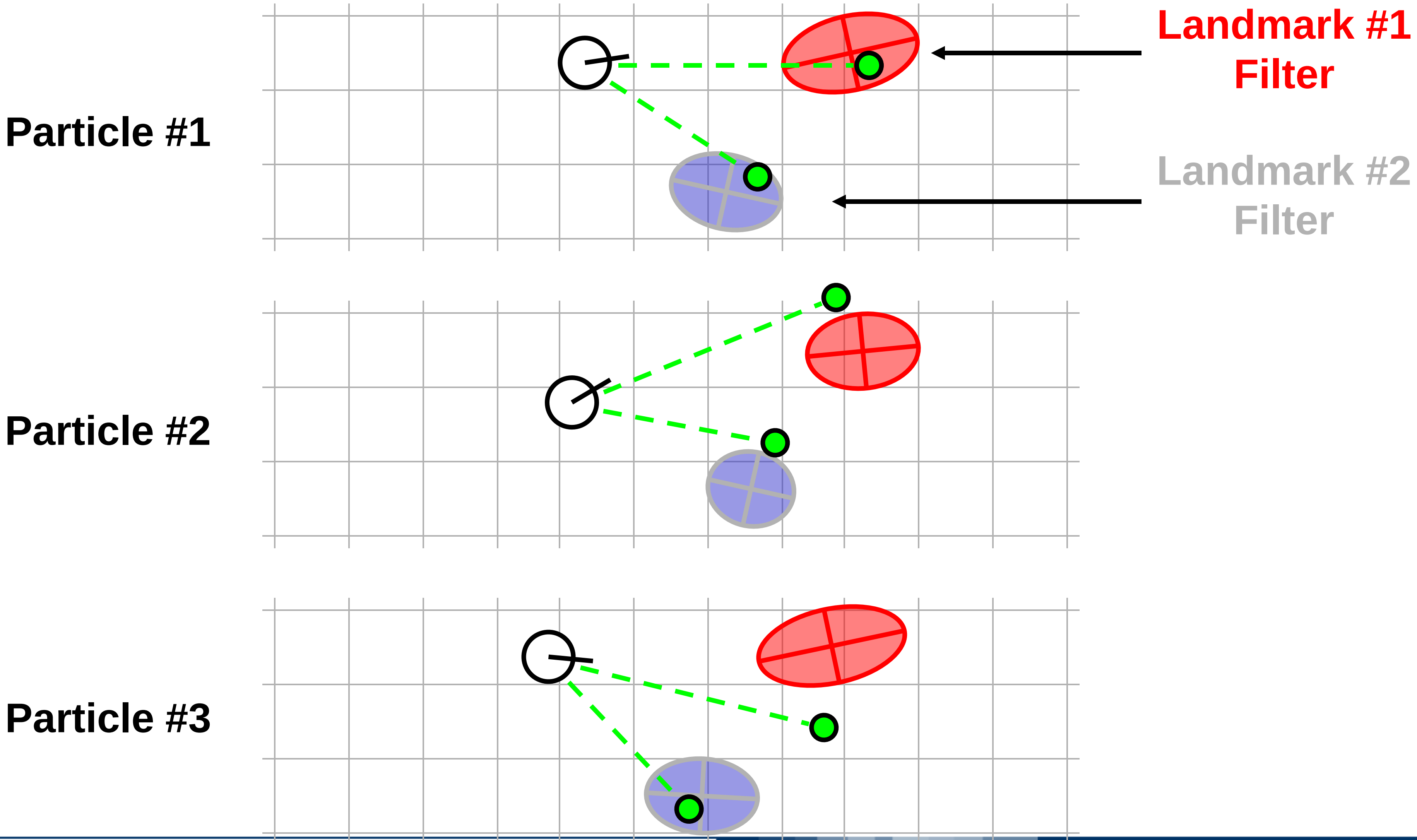
Landmark #1 Filter

Landmark #2 Filter

Particle #2

Particle #3

FastSLAM – Sensor Update



Particle #1

Landmark #1 Filter

Landmark #2 Filter

Particle #2

Particle #3

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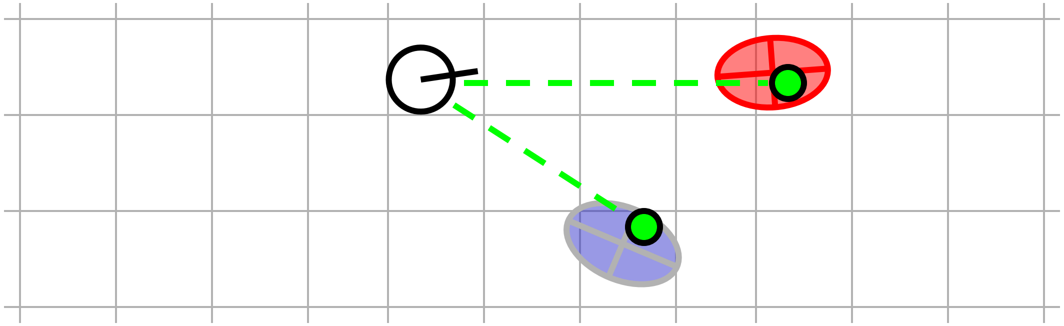
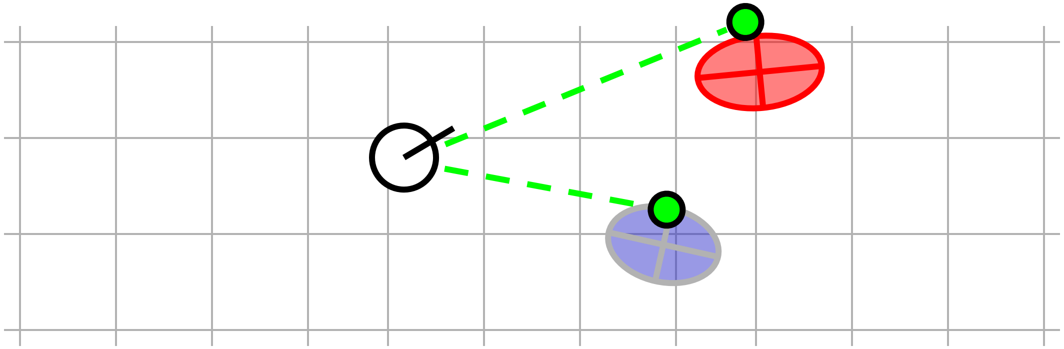
FastSLAM – Sensor Update

Particle #1



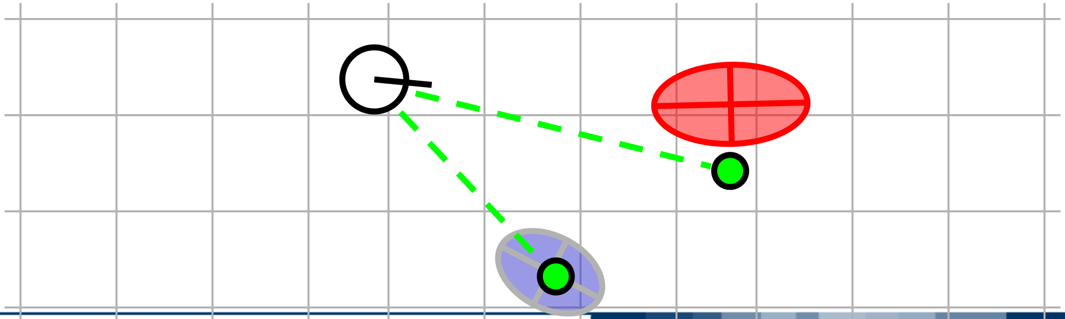
Weight = 0.8

Particle #2



Weight = 0.4

Particle #3



Weight = 0.1

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FastSLAM Complexity

Update robot particles based on control u_{t-1}

$O(N)$

Constant time per particle

Incorporate observation z_t into Kalman filters

$O(N \cdot \log(M))$

Log time per particle

Resample particle set

$O(N \cdot \log(M))$

Log time per particle

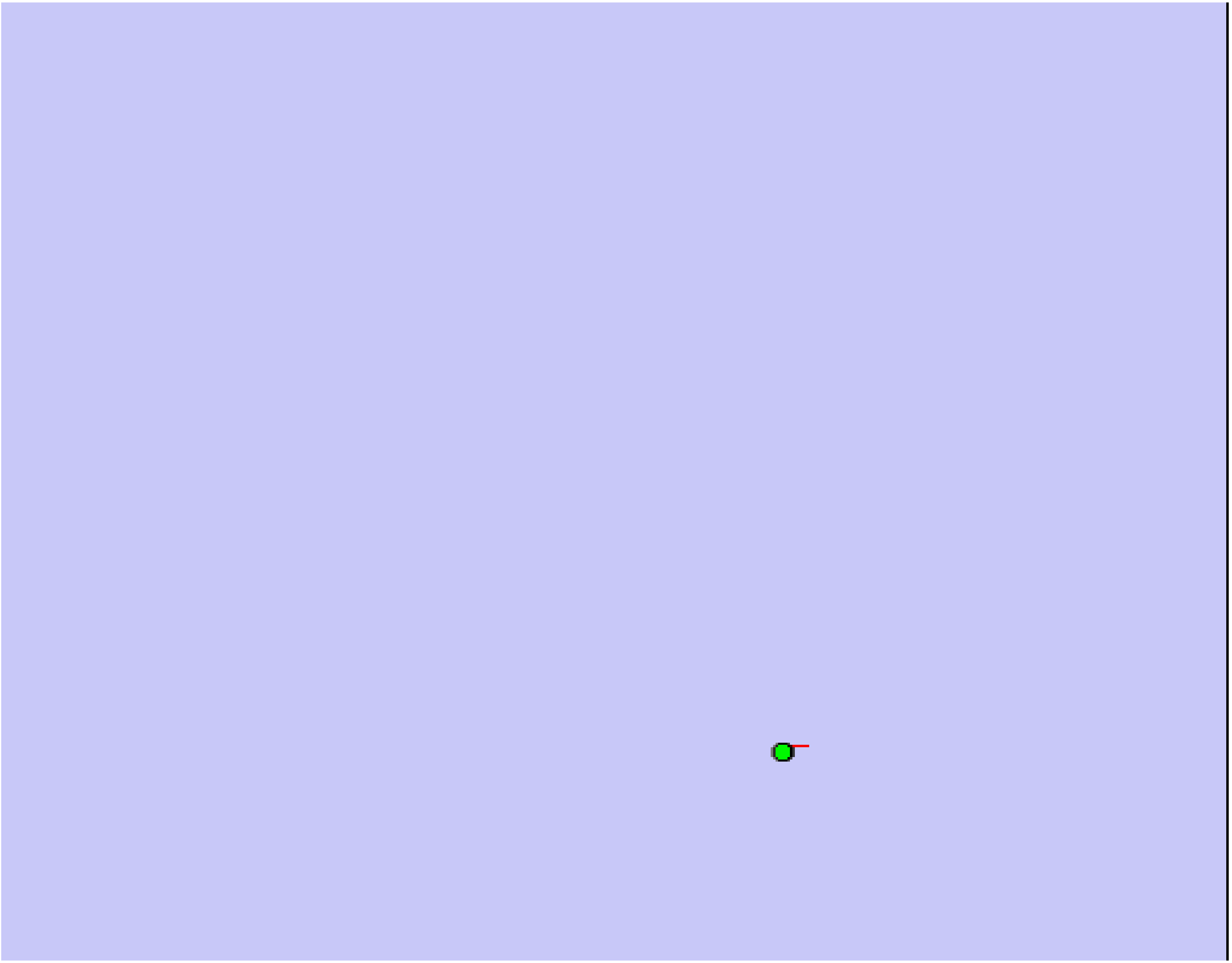
$O(N \cdot \log(M))$

Log time per particle

N = Number of particles

M = Number of map features

Fast-SLAM Example



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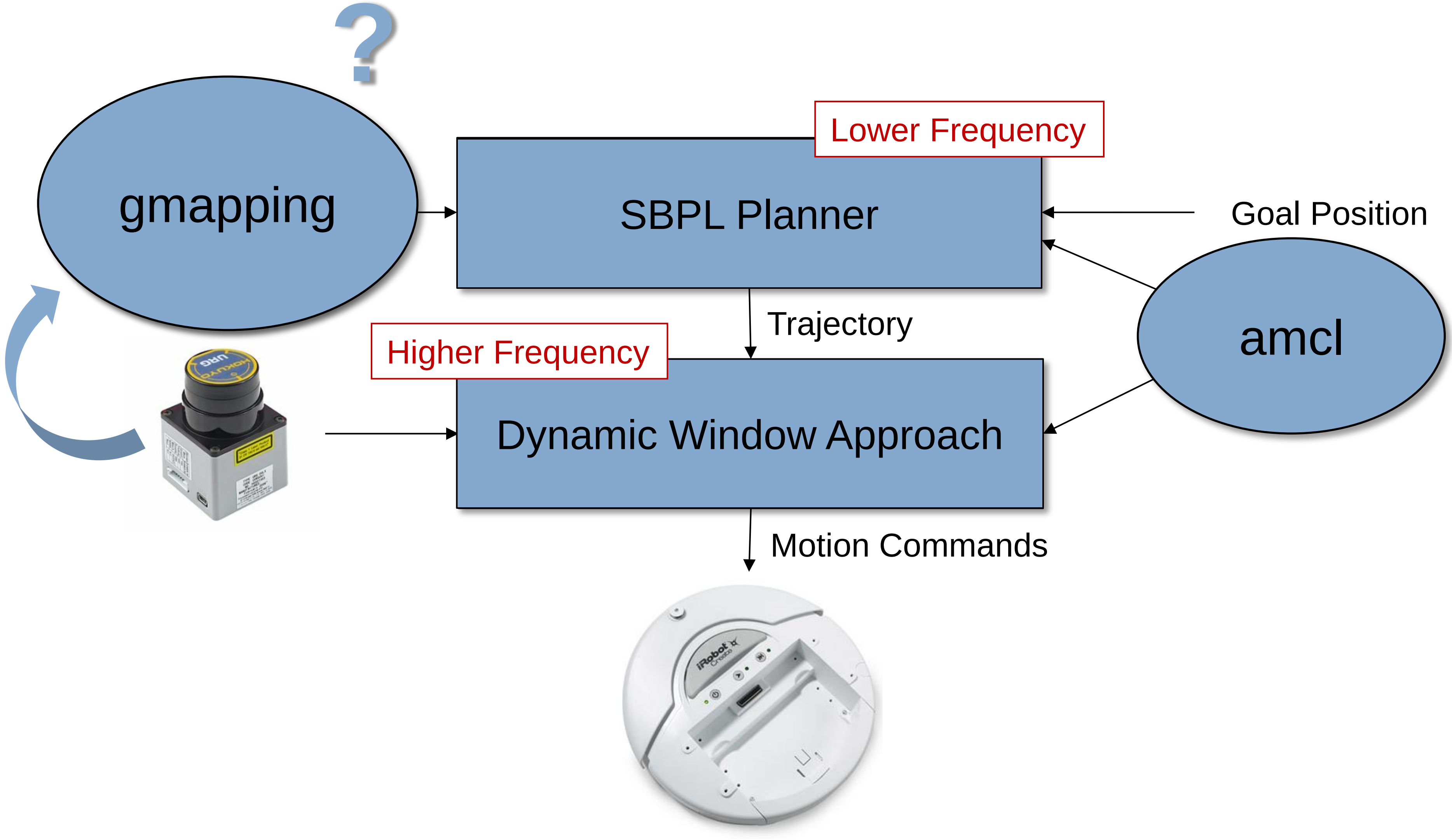
Recall the Two Layered Approach



?

gmapping

Lower Frequency

SBPL Planner

Goal Position

amcl

Trajectory

Higher Frequency

Dynamic Window Approach

Motion Commands

POLITECNICO DI MILANO

Cognitive Robotics –SLAM with Lasers

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