Intelligent Robots Practice

SLAM (Simultaneous Localization and Mapping)

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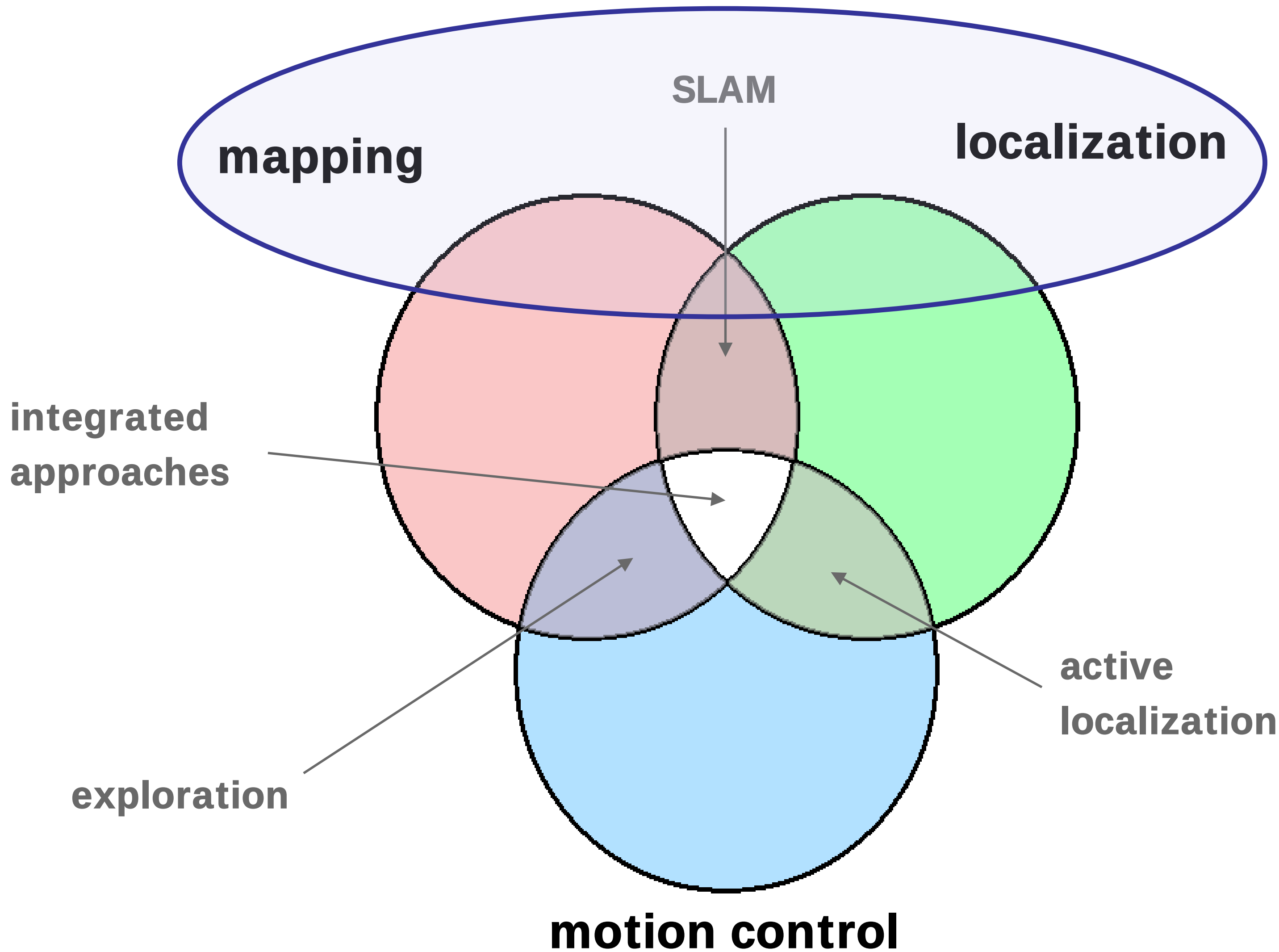
Contents

- The SLAM problem
- Issues in SLAM

The SLAM problem

The SLAM Problem



The SLAM Problem

$u_{1:n}$: control input
$z_{1:n}$: measurement
m : map
$x_{1:n}$: robot state

- Navigation Problems
  - Map building problems

$$m^* = \underset{m}{argmax}\ P(m|u_1, z_1, u_2, z_2 \dots u_n, z_n)$$

  - Localization problems

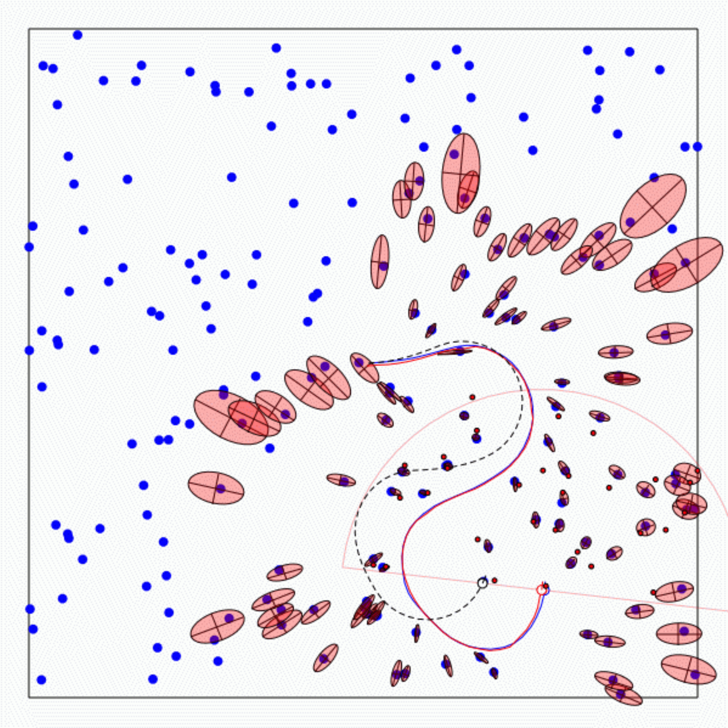
$$P(x_n|u_1, z_1, u_2, z_2 \dots u_n, z_n)$$

  - SLAM (Simultaneous Localization And Mapping) problems

$$P(x_{1:n}, m|u_1, z_1, u_2, z_2 \dots u_n, z_n)$$

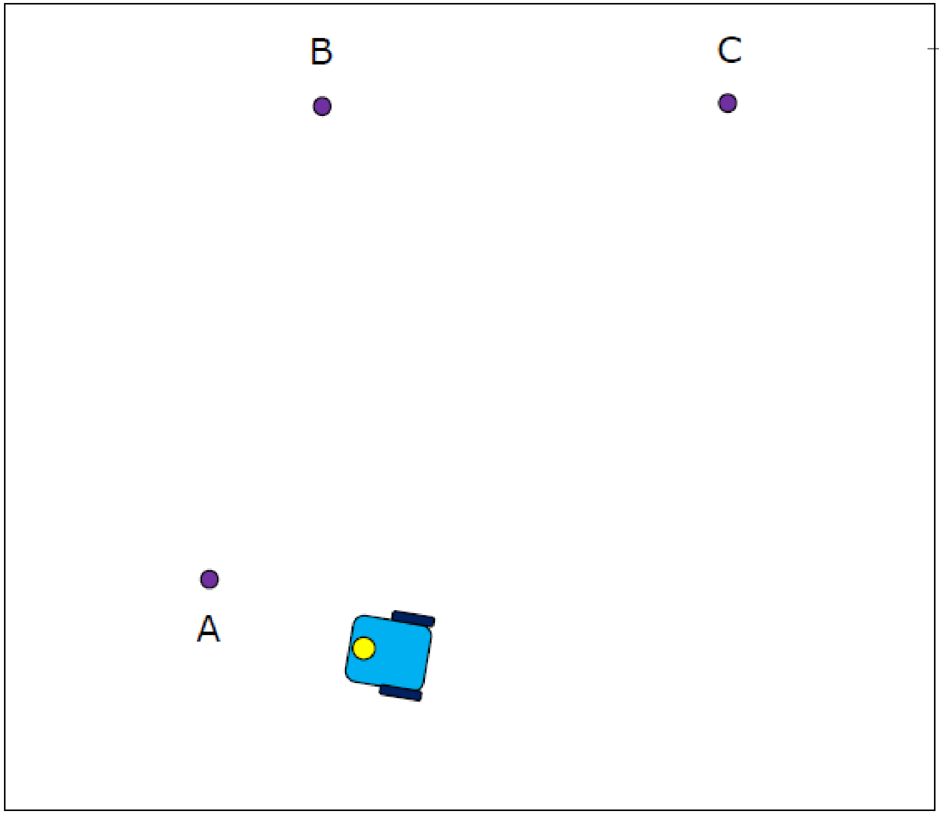
The SLAM Problem

- A robot is exploring an unknown, static environment.
  - Given:
    - The robot's controls
    - Observations of nearby features
  - Estimate:
    - Map of features
    - Path of the robot



The SLAM Problem

- How to do SLAM
  - Use internal representations for the positions of landmarks (: map)
  - Assumption: Robot’s uncertainty at starting position is zero



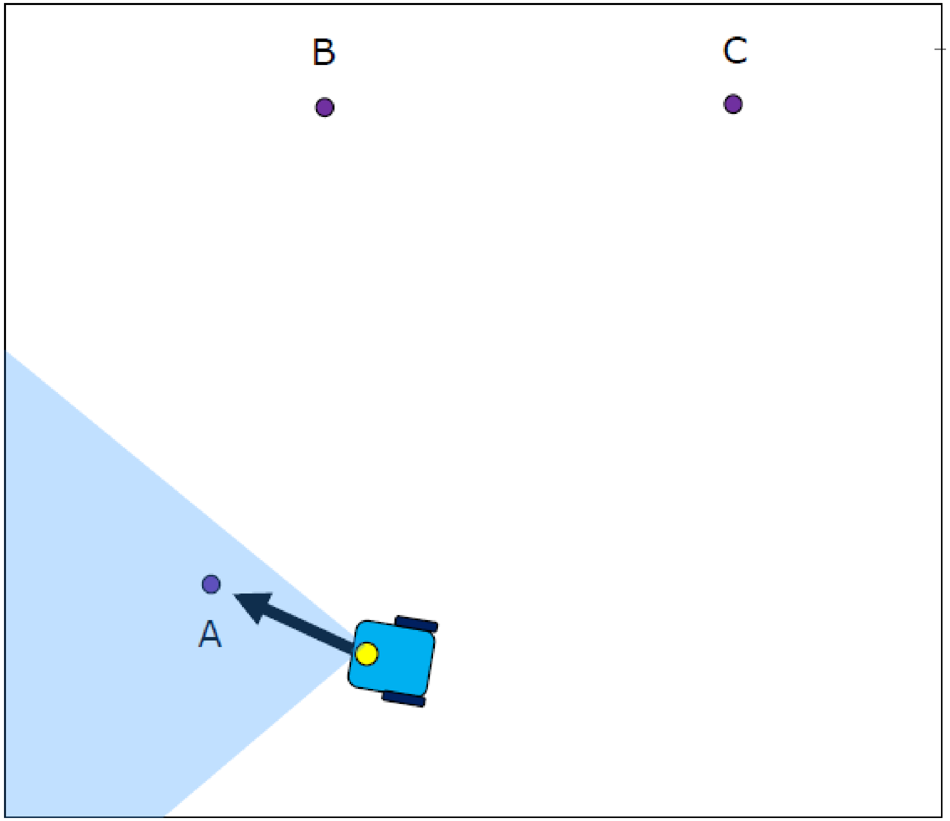
Start: robot has zero uncertainty

The SLAM Problem

- How to do SLAM

On every frame:

- **Predict** how the robot has moved
- **Measure**
- **Update** the internal representations

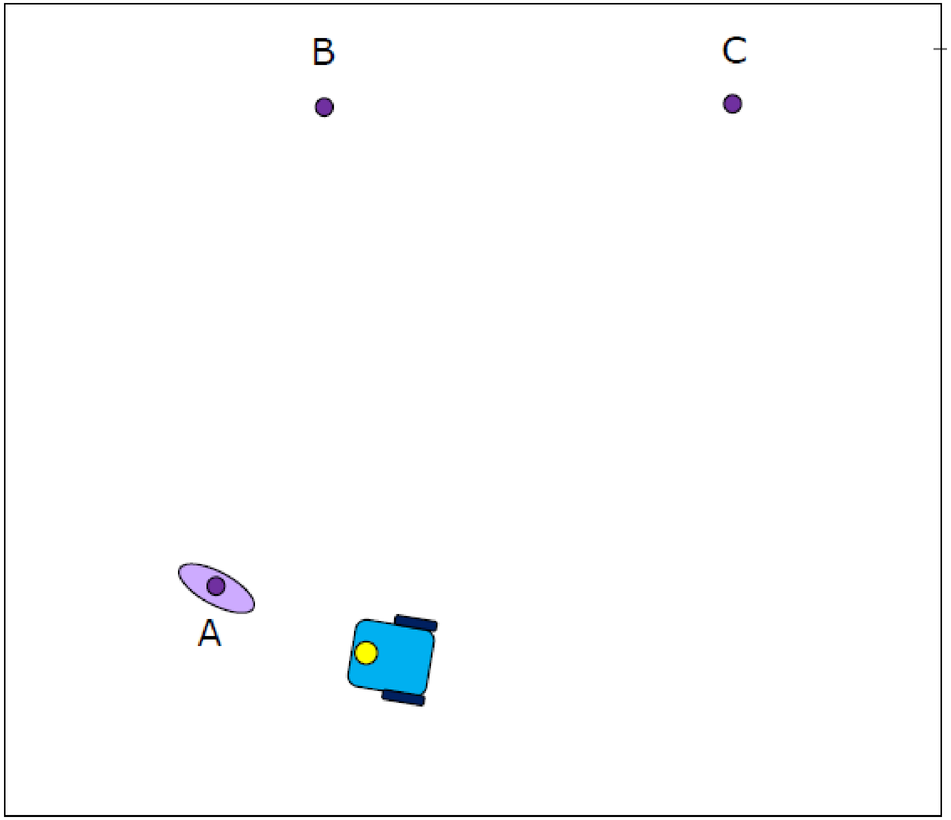


First measurement of feature A

The SLAM Problem

- How to do SLAM
  - The robot observes a feature which is mapped with an uncertainty related to the **measurement model**

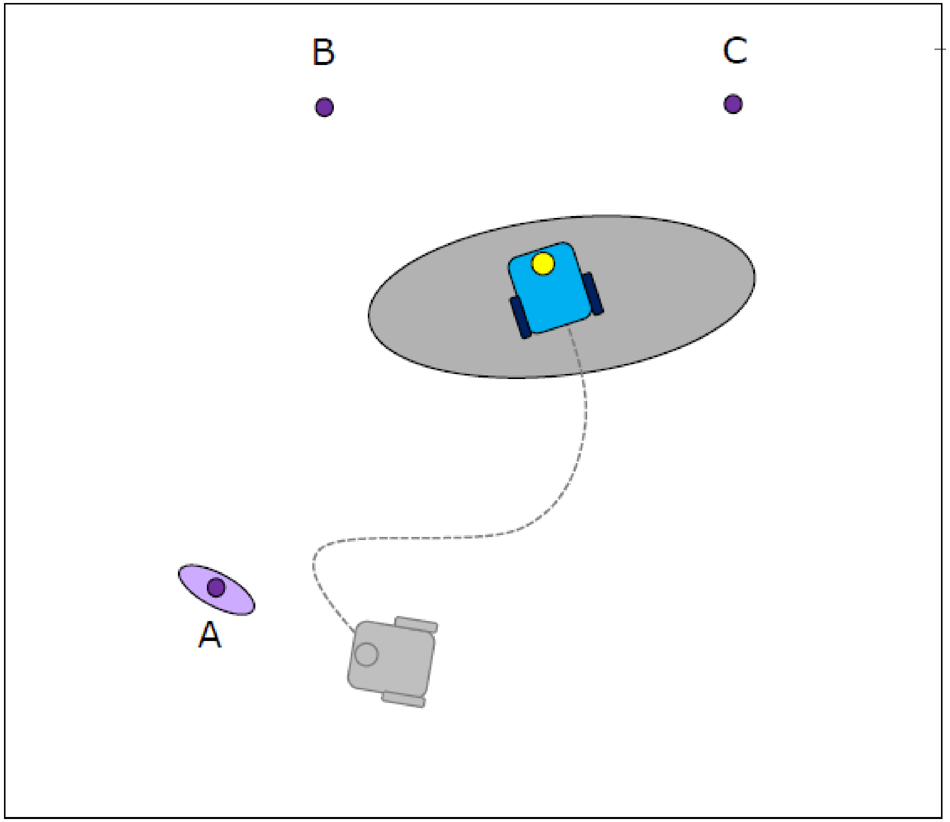
On every frame:
- **Predict** how the robot has moved
- **Measure**
- **Update** the internal representations



The SLAM Problem

- How to do SLAM
  - As the robot moves, its pose uncertainty increases, obeying the robot's **motion model**.

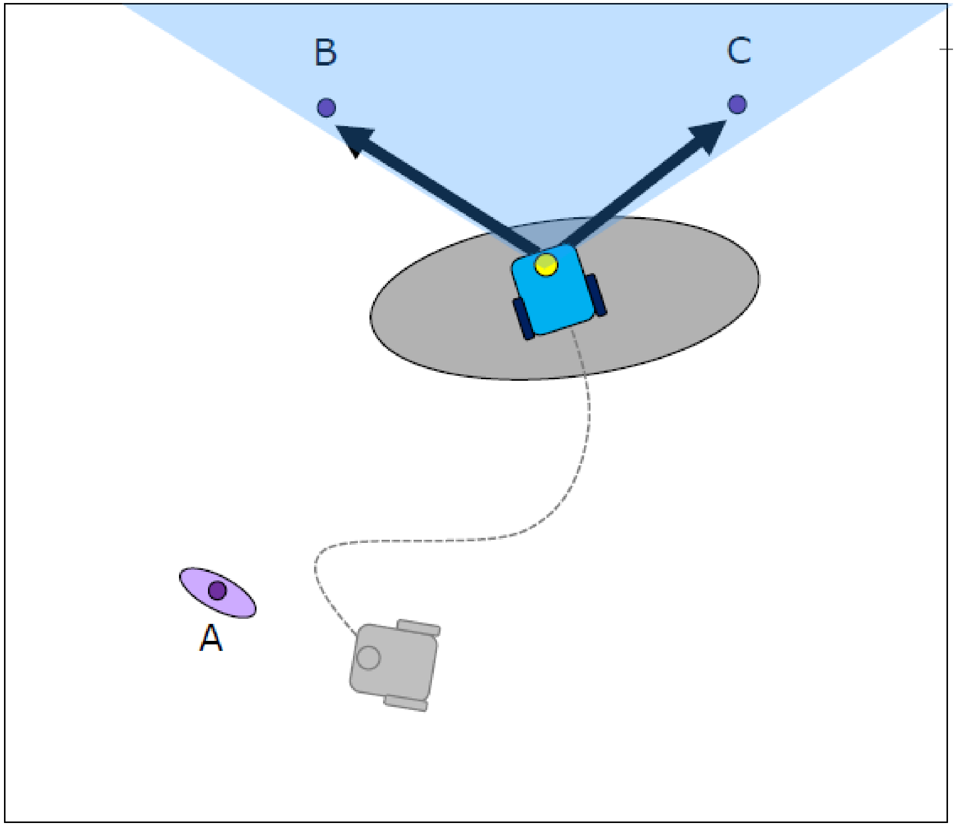
On every frame:
- **Predict** how the robot has moved
- **Measure**
- **Update** the internal representations



Robot moves forwards: uncertainty grows

The SLAM Problem

- How to do SLAM
  - Robot observes two new features.



Robot makes first measurements of B & C

On every frame:

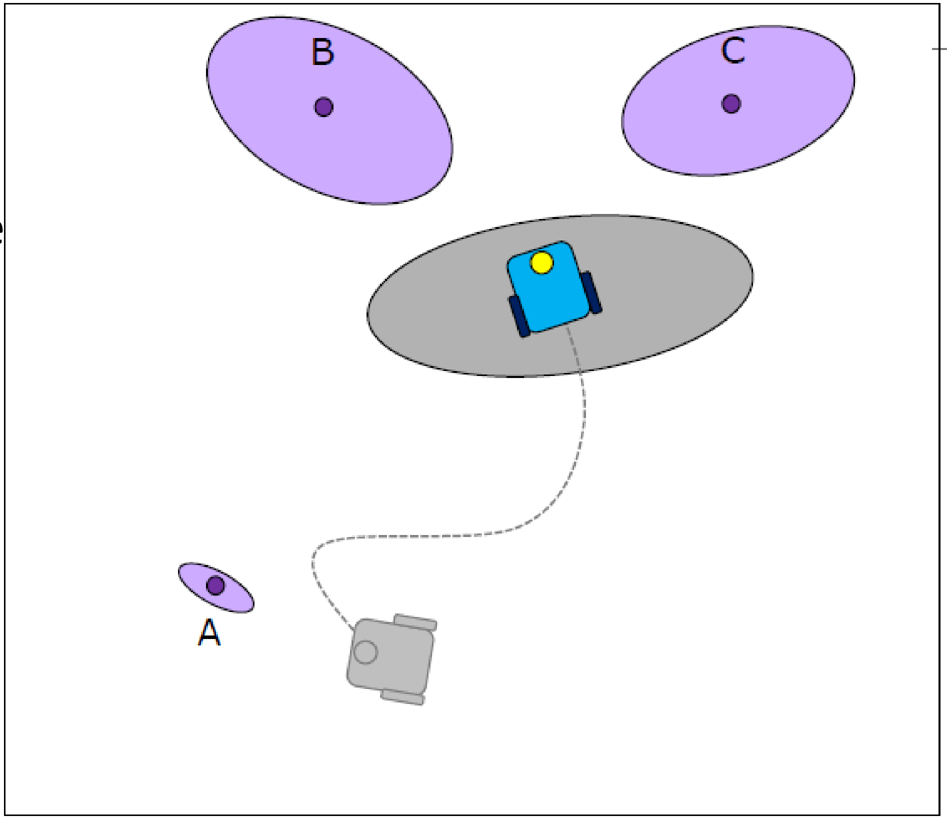
- **Predict** how the robot has moved
- **Measure**
- **Update** the internal representations

The SLAM Problem

- How to do SLAM
  - Their position uncertainty results from the **combination** of the measurement error with the robot pose uncertainty.

    → map becomes **correlated** with the robot pose estimate.

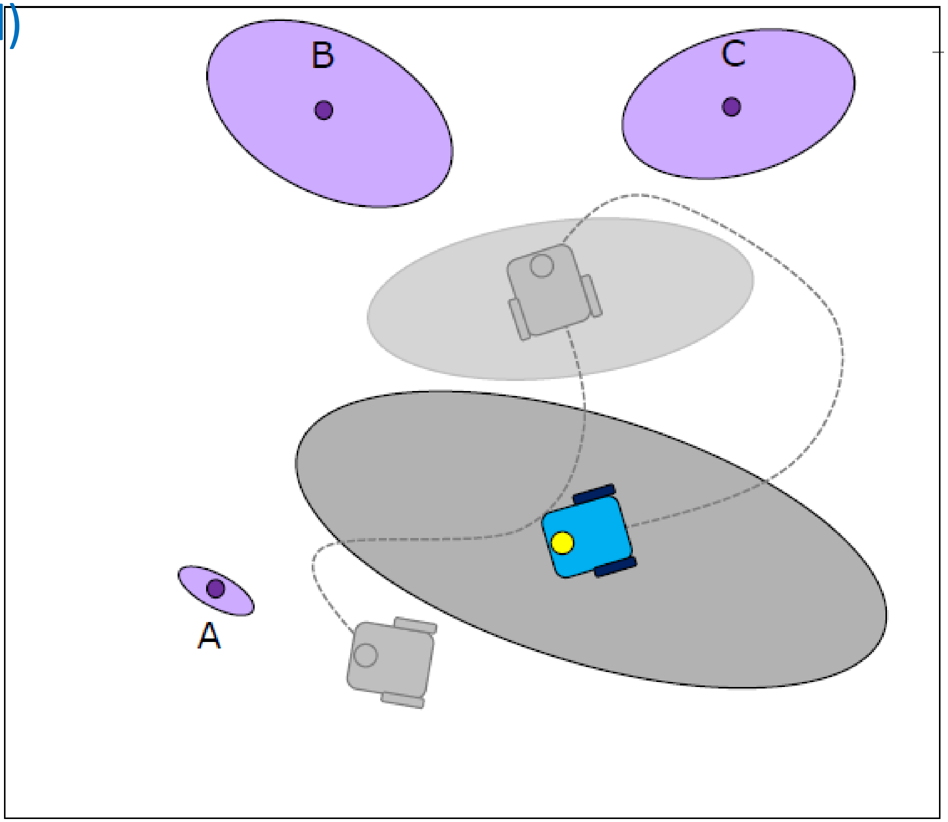
On every frame:
- **Predict** how the robot has moved
- **Measure**
- **Update** the internal representations



Robot makes first measurements of B & C

The SLAM Problem

- How to do SLAM
  - Robot moves again and its uncertainty increases (motion model)



Robot moves again: uncertainty grows more

On every frame:

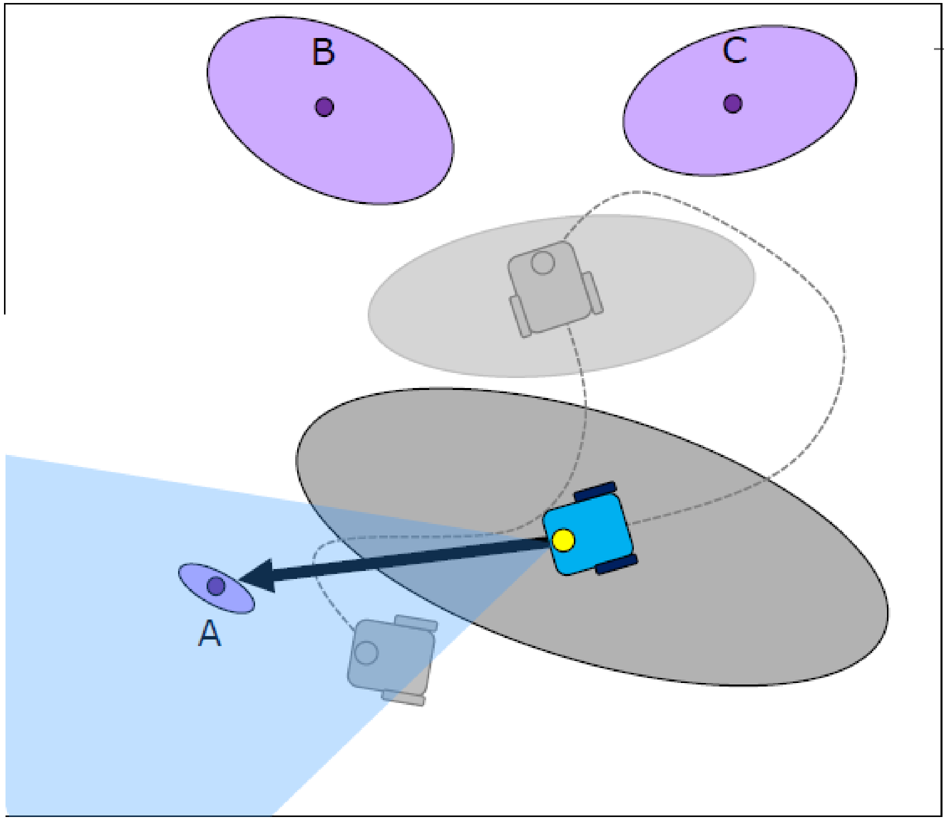
- **Predict** how the robot has moved
- **Measure**
- **Update** the internal representations

The SLAM Problem

- How to do SLAM
  - Robot re-observes an old feature → **Loop closure** detection

On every frame:

- **Predict** how the robot has moved
- **Measure**
- **Update** the internal representations



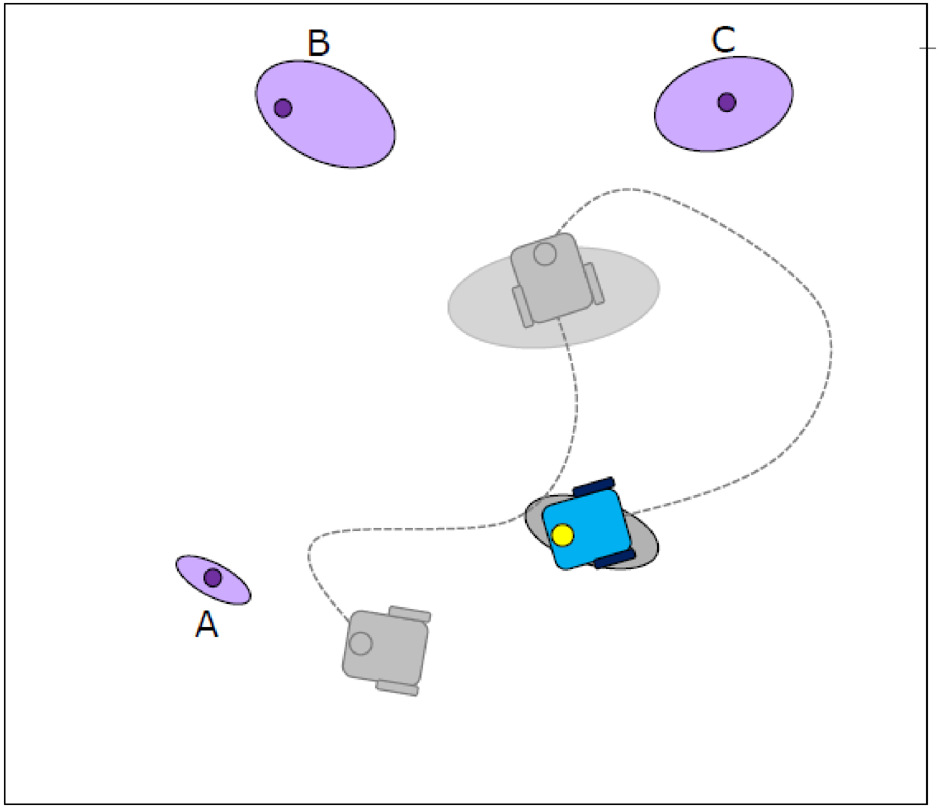
Robot re-measures A: "loop closure"

The SLAM Problem

- How to do SLAM
  - Robot updates its position: the resulting **pose** estimate becomes **correlated** with the feature **location estimates**.
  - Robot's uncertainty **shrinks** and so does the uncertainty in the rest of the map

On every frame:

- **Predict** how the robot has moved
- **Measure**
- **Update** the internal representations



Robot re-measures A: "loop closure"
uncertainty shrinks

The SLAM Problem

- SLAM: **S**imultaneous **L**ocalization **A**nd **M**apping
  - Full SLAM:
    - Estimates entire path and map

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

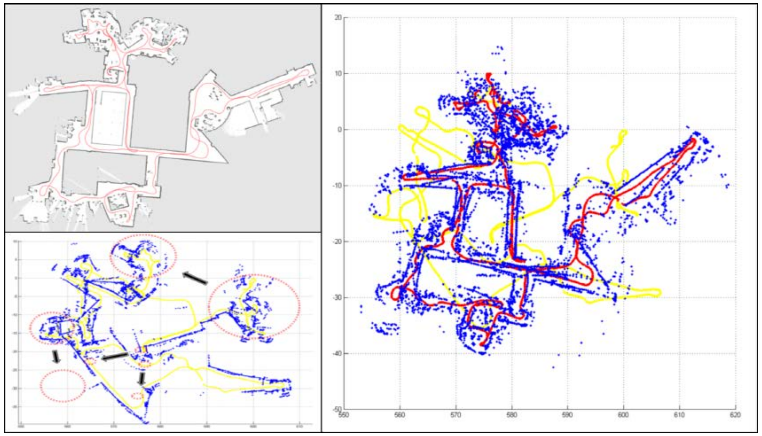
  - Online SLAM:
    - Estimates most recent pose and map

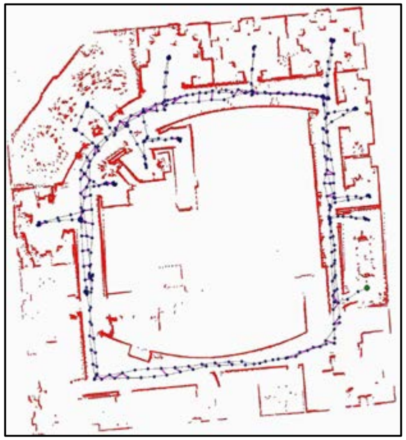
$$p(x_t, m \mid z_{1:t}, u_{1:t}) = \iint \dots \int p(x_{1:t}, m \mid z_{1:t}, u_{1:t})\, dx_1 dx_2 \dots dx_{t-1}$$

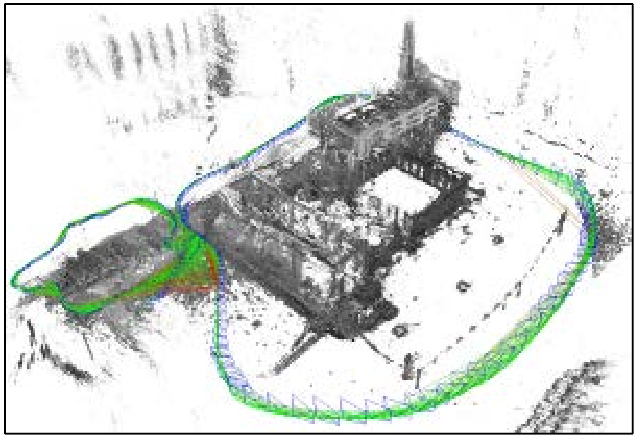
Issues in SLAM

Issues in SLAM

- Basic SLAM Paradigms
  - Filtering Based Approaches
    - EKF SLAM
    - Particle Filter SLAM (FastSLAM, RBPF SLAM)
  - Optimization Based Approaches
    - Graph-based SLAM







Issues in SLAM

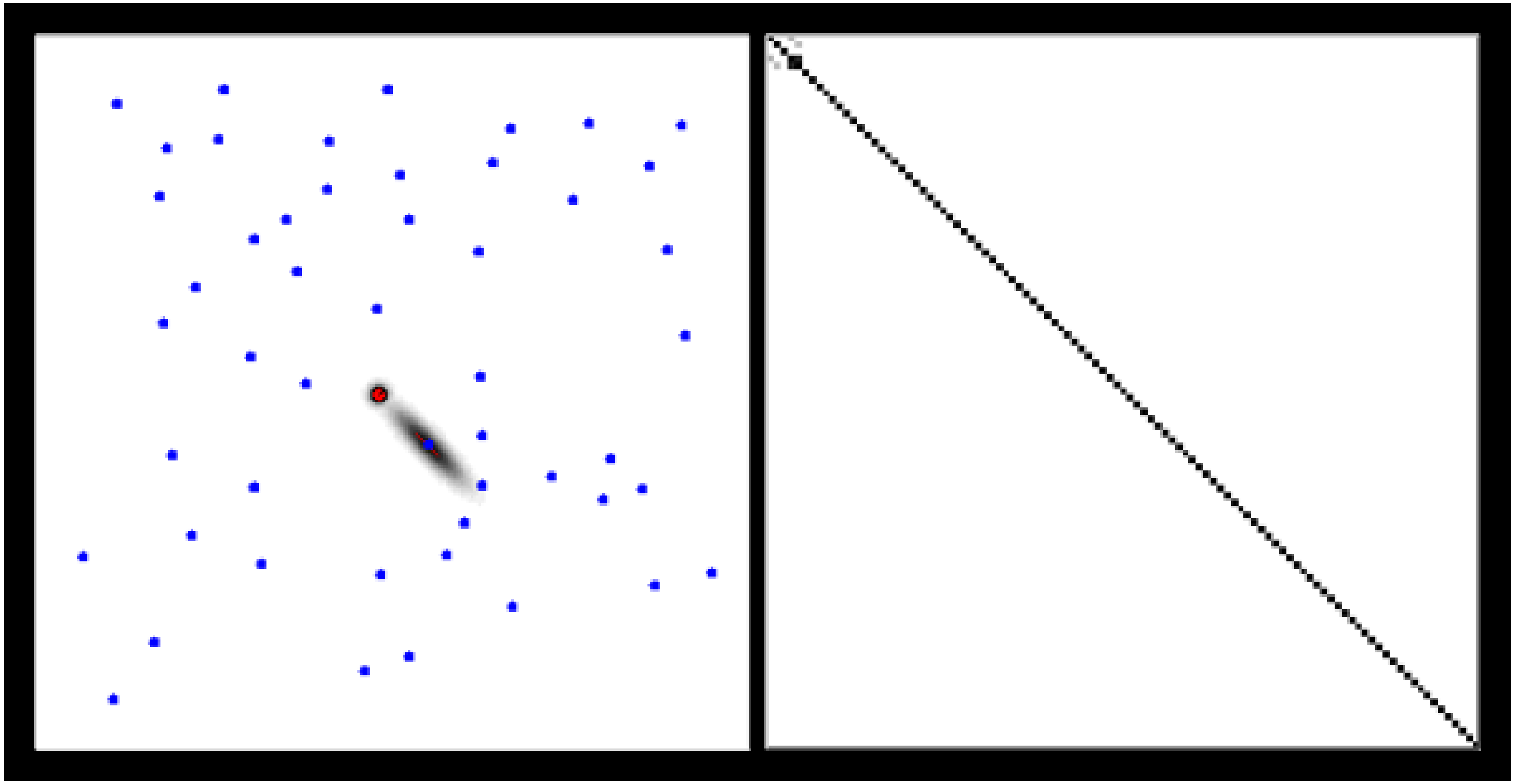
- Filtering Based Approaches
  - EKF SLAM
    - Map with N landmarks:(3+2N)-dimensional Gaussian

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

    - Can handle hundreds of dimensions

Issues in SLAM

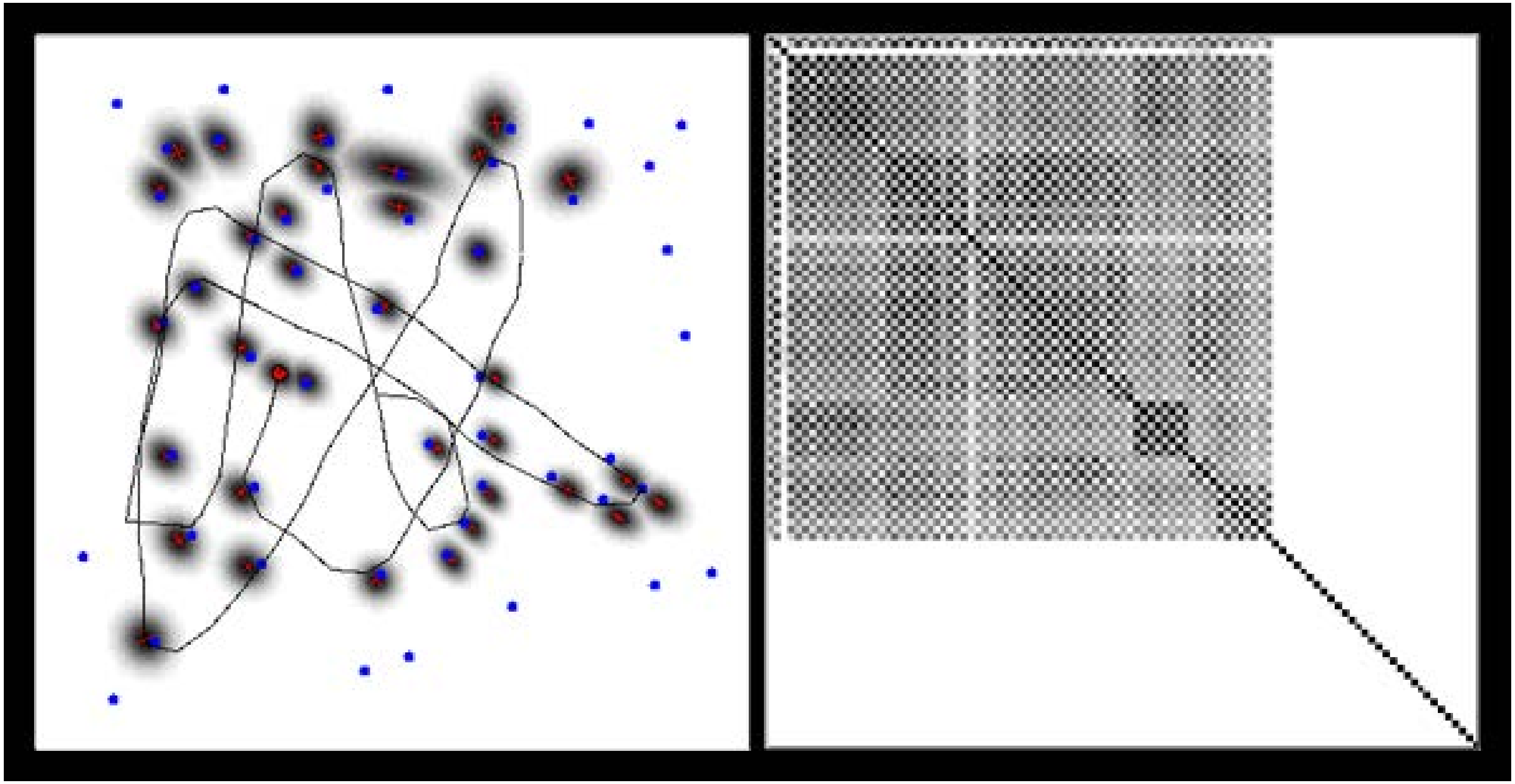
- Filtering Based Approaches
  - EKF SLAM



Map　　　　　　　　Correlation matrix

Issues in SLAM

- Filtering Based Approaches
  - EKF SLAM

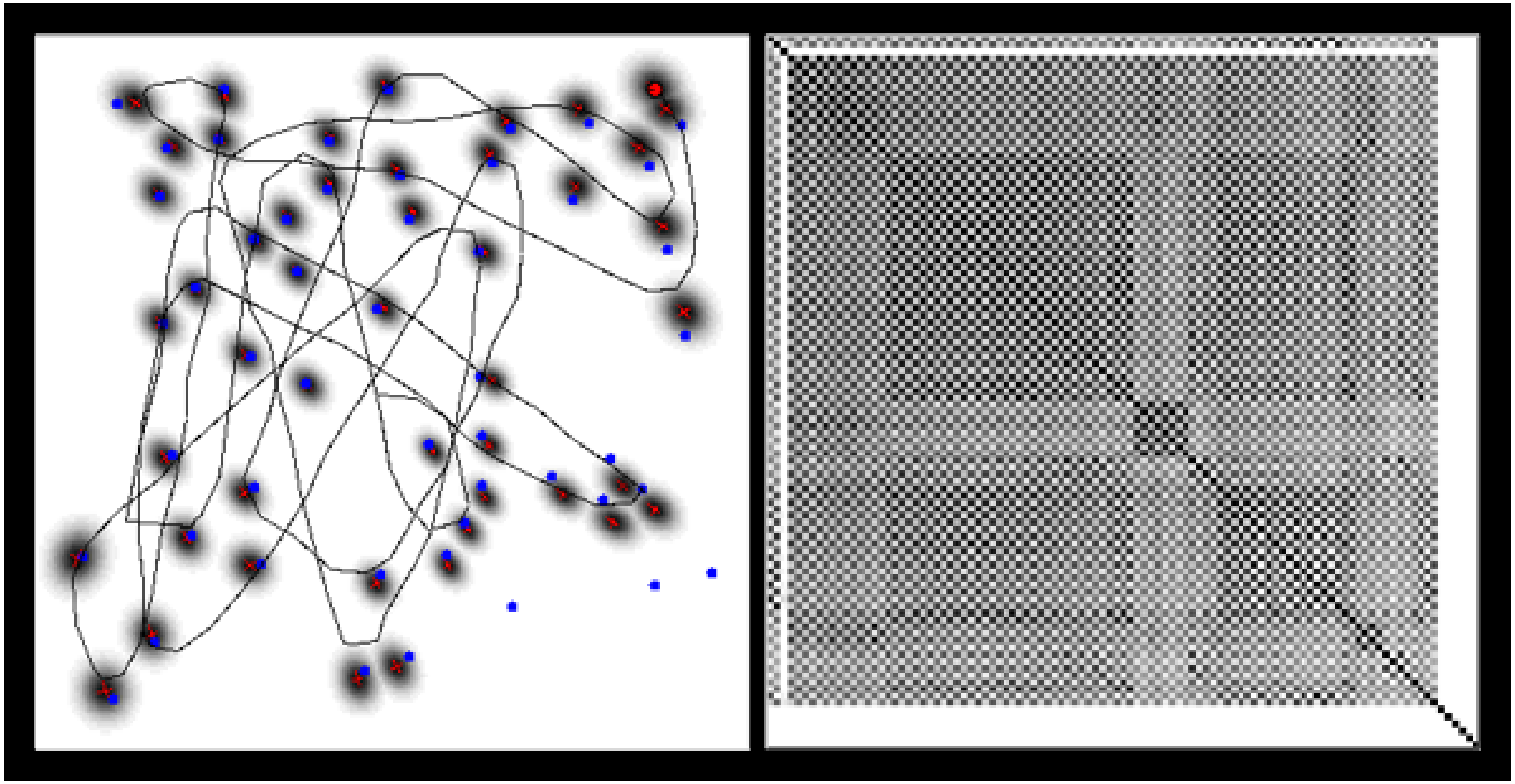


Map

Correlation matrix

Issues in SLAM

- Filtering Based Approaches
  - EKF SLAM

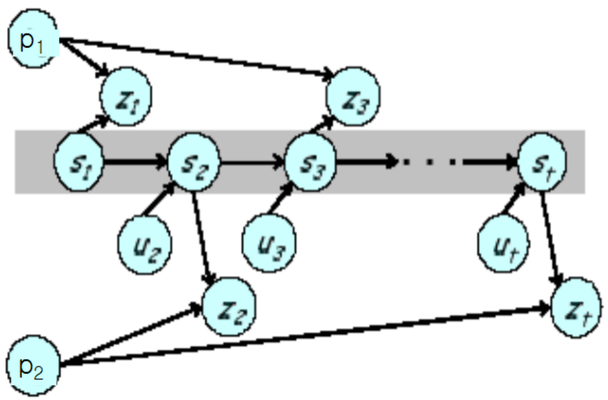


Map Correlation matrix

Issues in SLAM

Filtering Based Approaches

Particle Filter SLAM (FastSLAM, RBPF SLAM)



- Measurement : $z^t = \{z_1, z_2, \cdots, z_t\}$
- States : $s^t = \{s_1, s_2, \cdots, s_t\}$
- Control input : $u^t = \{u_1, u_2, \cdots, u_t\}$
- Landmarks : $P = \{p_1, p_2, \cdots, p_N\}$

M particles & N landmarks in the particle filter

	Robot Pose	Landmark 1	Landmark 2		Landmark N
Particle 1:	x y p	μ_1 Σ_1	μ_2 Σ_2	. . .	μ_N Σ_N
Particle 2:	x y p	μ_1 Σ_1	μ_2 Σ_2	. . .	μ_N Σ_N
⋮					
Particle M:	x y p	μ_1 Σ_1	μ_2 Σ_2	. . .	μ_N Σ_N

2nd particle

$$S_t^{[2]} = < s^{t,[2]}, \mu_{1,t}^{[2]}, \Sigma_{1,t}^{[2]}, \cdots, \mu_{N,t}^{[2]}, \Sigma_{N,t}^{[2]} >$$

Issues in SLAM

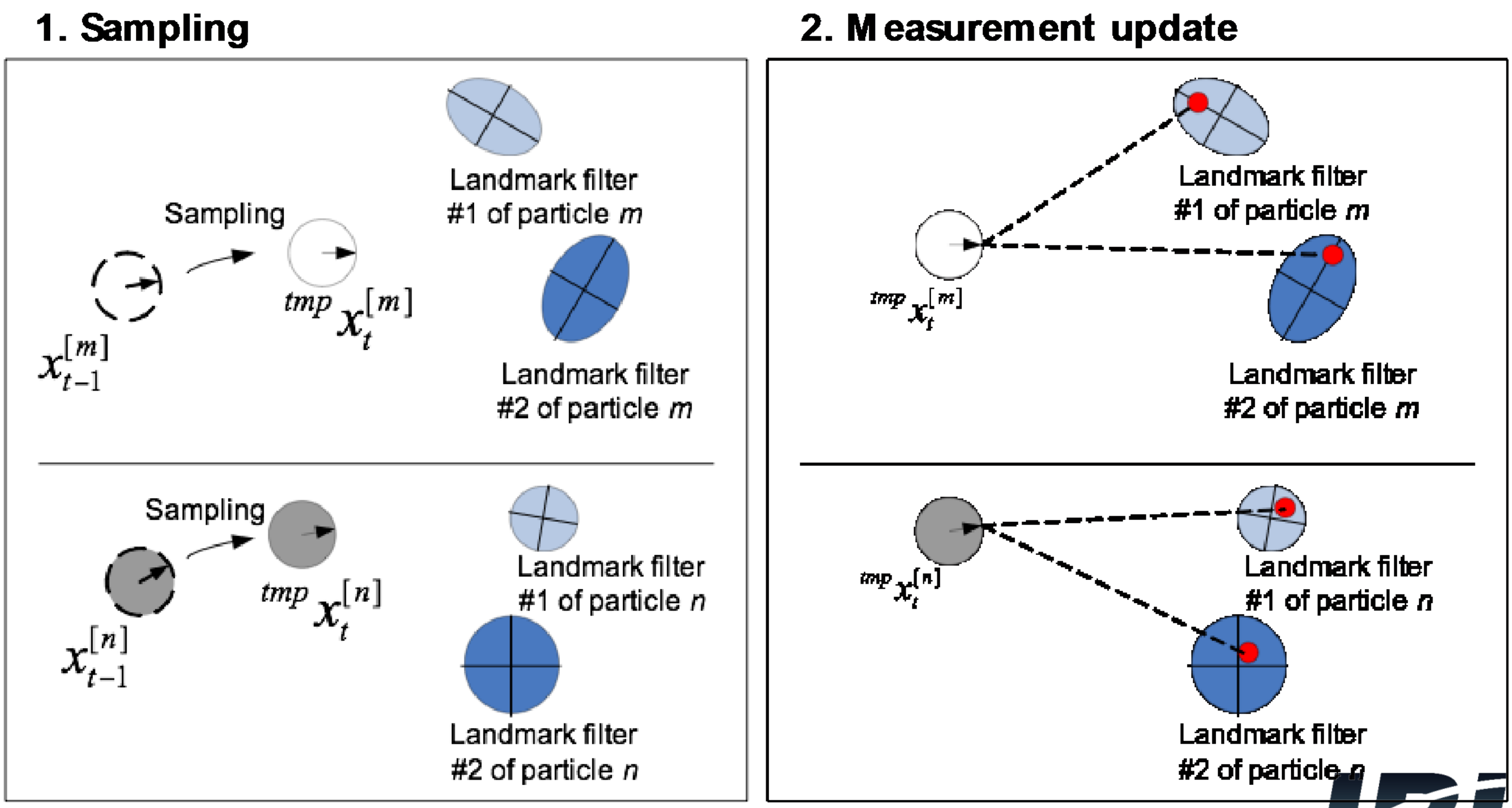
- Particle Filter SLAM (FastSLAM, RBPF SLAM)

$$
\begin{aligned}
& p(x_{1:t}, l_{1:m} \mid z_{1:t}, u_{0:t-1}) \\
& \quad = p(x_{1:t} \mid z_{1:t}, u_{0:t-1}) \cdot p(l_{1:m} \mid x_{1:t}, z_{1:t}) \\
& \quad = \underbrace{p(x_{1:t} \mid z_{1:t}, u_{0:t-1})}_{\text{Robot path posterior (localization problem)}} \cdot \underbrace{\prod_{i=1}^{M} p(l_i \mid x_{1:t}, z_{1:t})}_{\text{Conditionally independent landmark positions}}
\end{aligned}
$$

- Robot Path Posterior
  - Estimate a path posterior using a particle filter
- Landmark Estimators
  - Estimate each landmark using Extended Kalman Filter
  - All EKF filters are low-dimensional

Issues in SLAM

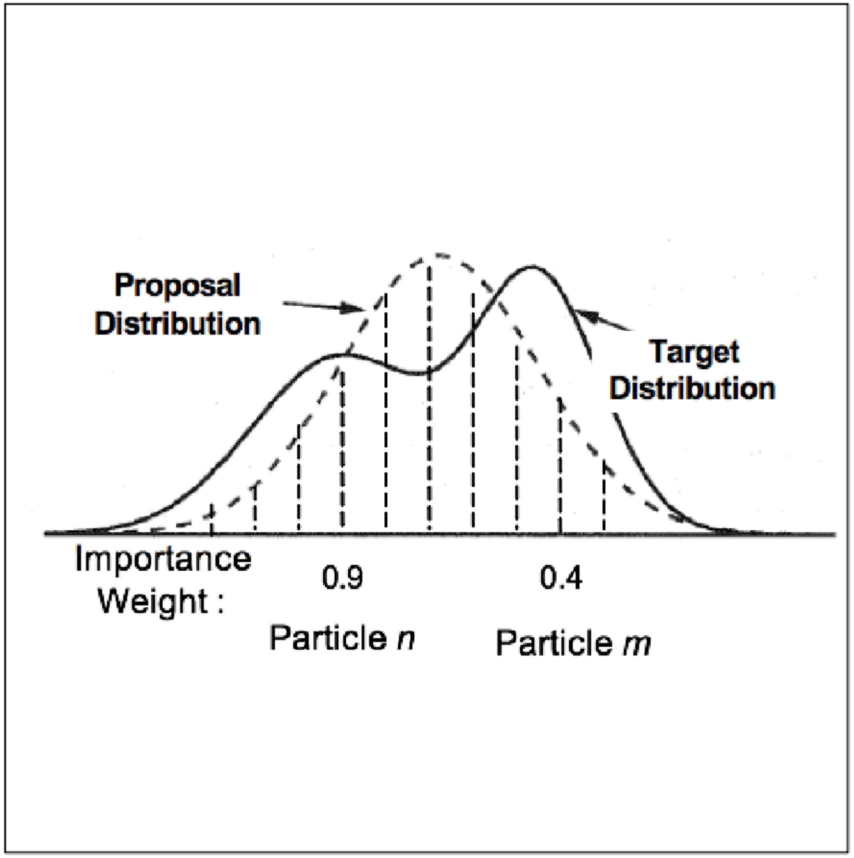
- Particle Filter SLAM (FastSLAM, RBPF SLAM)
  - Graphical Overview



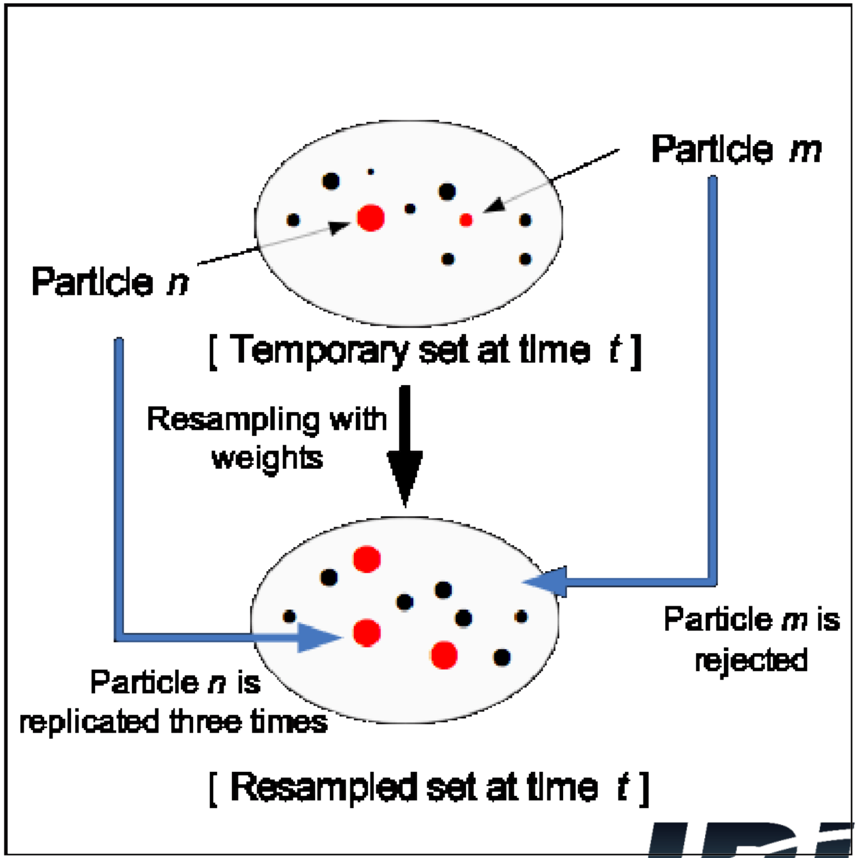
Issues in SLAM

- Particle Filter SLAM (FastSLAM, RBPF SLAM)
  - Graphical Overview

3. Importance weight



4. Resampling

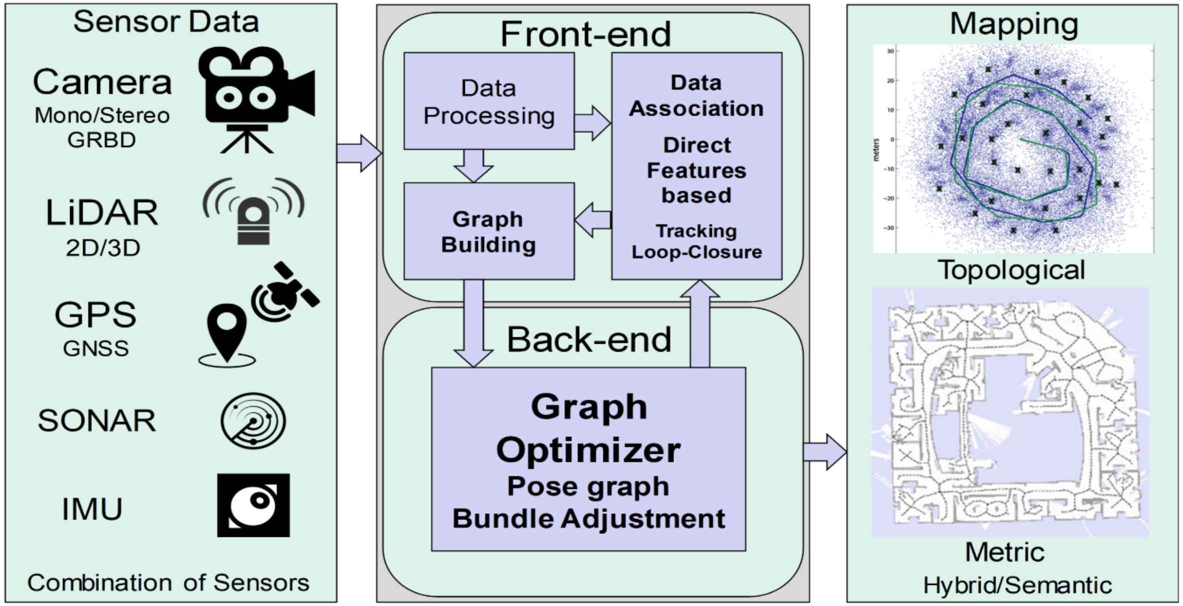


Issues in SLAM

- Modern SLAM
  - Graph based SLAM

$$\mathbf{x}^* = \underset{\mathbf{x}}{\operatorname{argmin}} \sum_{k=1}^{K} (h_k(\mathbf{x}) - z_k)^T \Omega_k (h_k(\mathbf{x}) - z_k)$$

    - Front-end: graph construction through raw measurements
    - Back-end: graph optimization



Issues in SLAM

- Modern SLAM
  - Semantic SLAM
    - An approach that includes the semantic information into the SLAM process
  - Challenging Issues in SLAM
    - Dynamic Environments
    - Loop Closure
    - Robust Perception
    - Semantic Reasoning