

Introduction to Mobile Robotics

SLAM: Simultaneous Localization and Mapping

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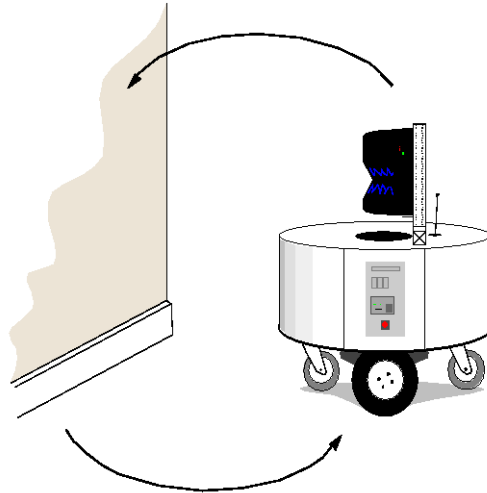


What is SLAM?

- Estimate the pose of a robot and the map of the environment at the same time
- SLAM is hard, because
 - a map is needed for localization and
 - a good pose estimate is needed for mapping
- **Localization:** inferring location given a map
- **Mapping:** inferring a map given locations
- **SLAM:** learning a map and locating the robot simultaneously

The SLAM Problem

- SLAM has long been regarded as a **chicken-or-egg** problem:
 - a map is needed for localization and
 - a pose estimate is needed for mapping



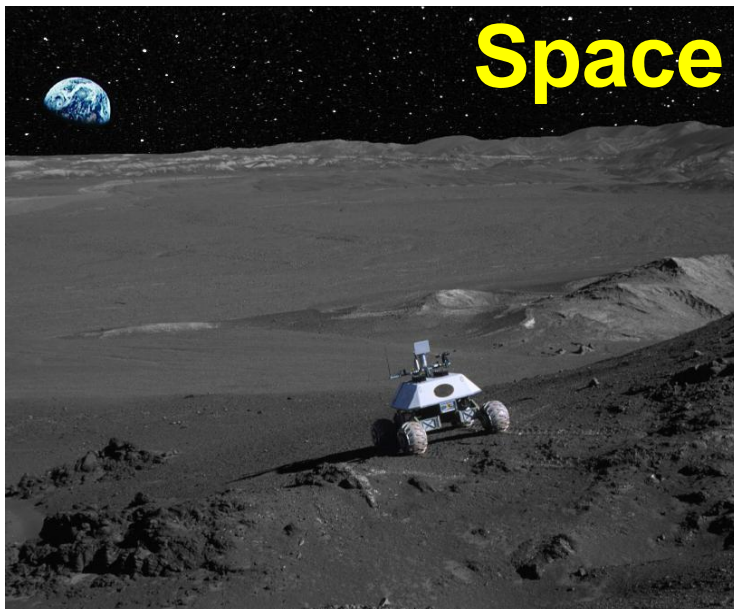
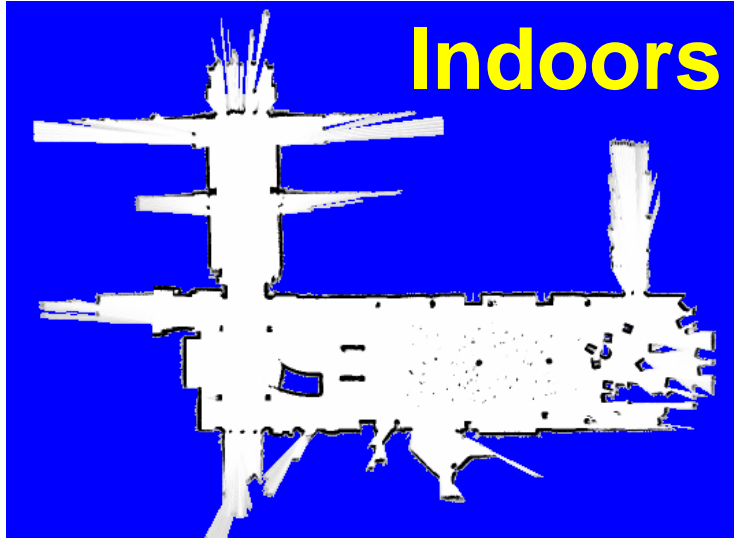
SLAM Applications

- SLAM is central to a range of indoor, outdoor, in-air and underwater applications for both manned and autonomous vehicles.

Examples:

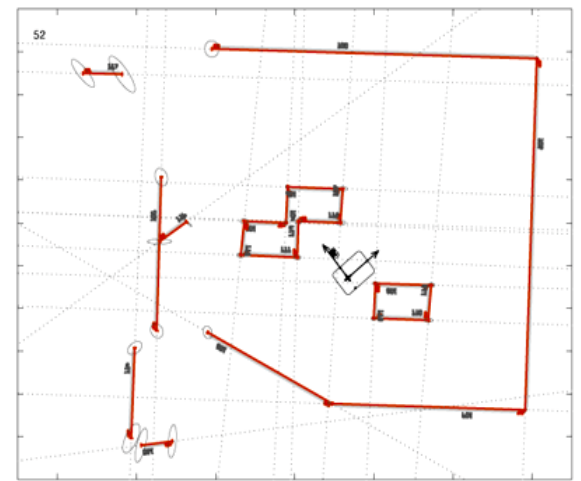
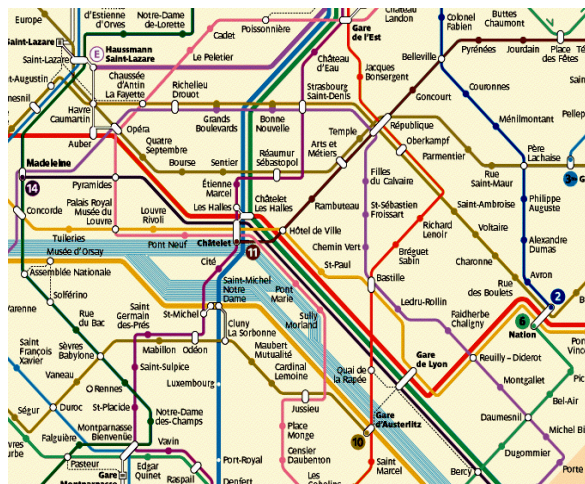
- At home: vacuum cleaner, lawn mower
- Air: surveillance with unmanned air vehicles
- Underwater: reef monitoring
- Underground: exploration of mines
- Space: terrain mapping for localization

SLAM Applications



Map Representations

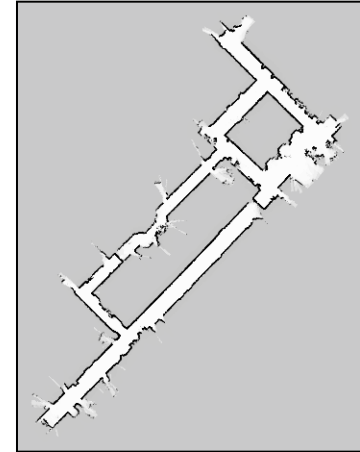
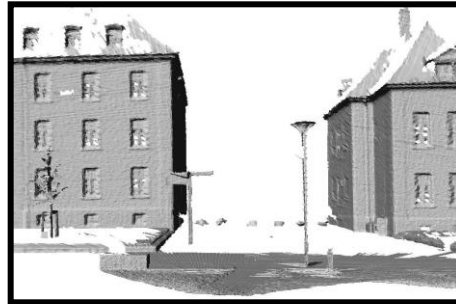
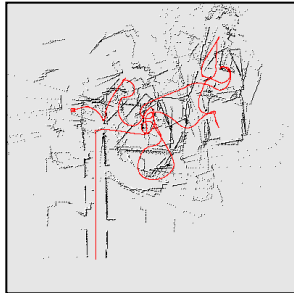
Examples: Subway map, city map, landmark-based map



Maps are **topological** and/or **metric models** of the environment

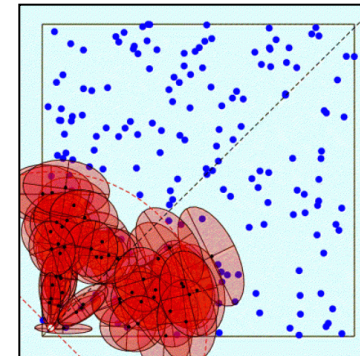
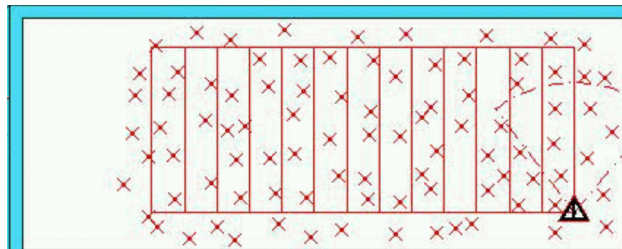
Map Representations in Robotics

- Grid maps or scans, 2d, 3d



[Lu & Milios, 97; Gutmann, 98; Thrun 98; Burgard, 99; Konolige & Gutmann, 00; Thrun, 00; Arras, 99; Haehnel, 01; Grisetti et al., 05; ...]

- Landmark-based



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

The SLAM Problem

- SLAM is considered a fundamental problem for robots to become truly autonomous
- Large variety of different SLAM approaches have been developed
- The majority uses probabilistic concepts
- History of SLAM dates back to the mid-eighties

Feature-Based SLAM

Given:

- The robot's controls

$$U_{1:k} = \{u_1, u_2, \dots, u_k\}$$

- Relative observations

$$Z_{1:k} = \{z_1, z_2, \dots, z_k\}$$

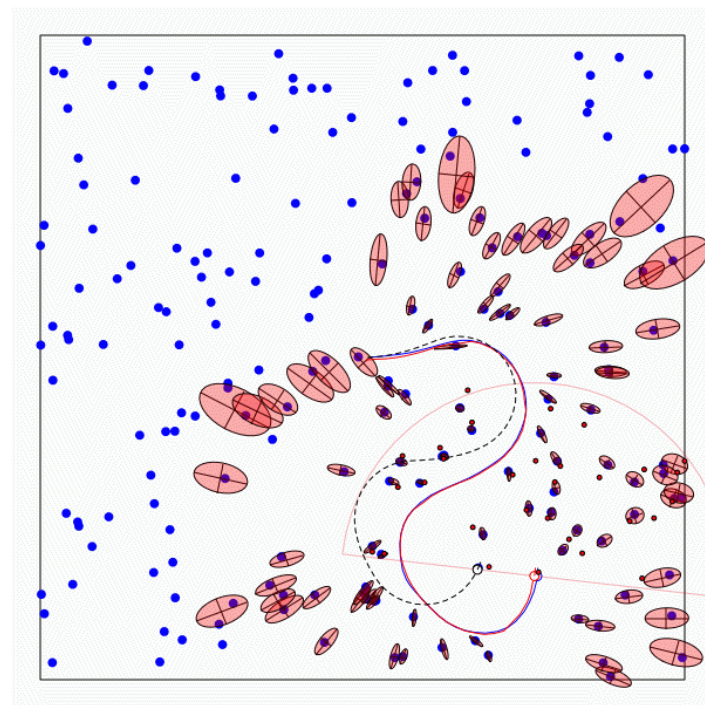
Wanted:

- Map of features

$$m = \{m_1, m_2, \dots, m_n\}$$

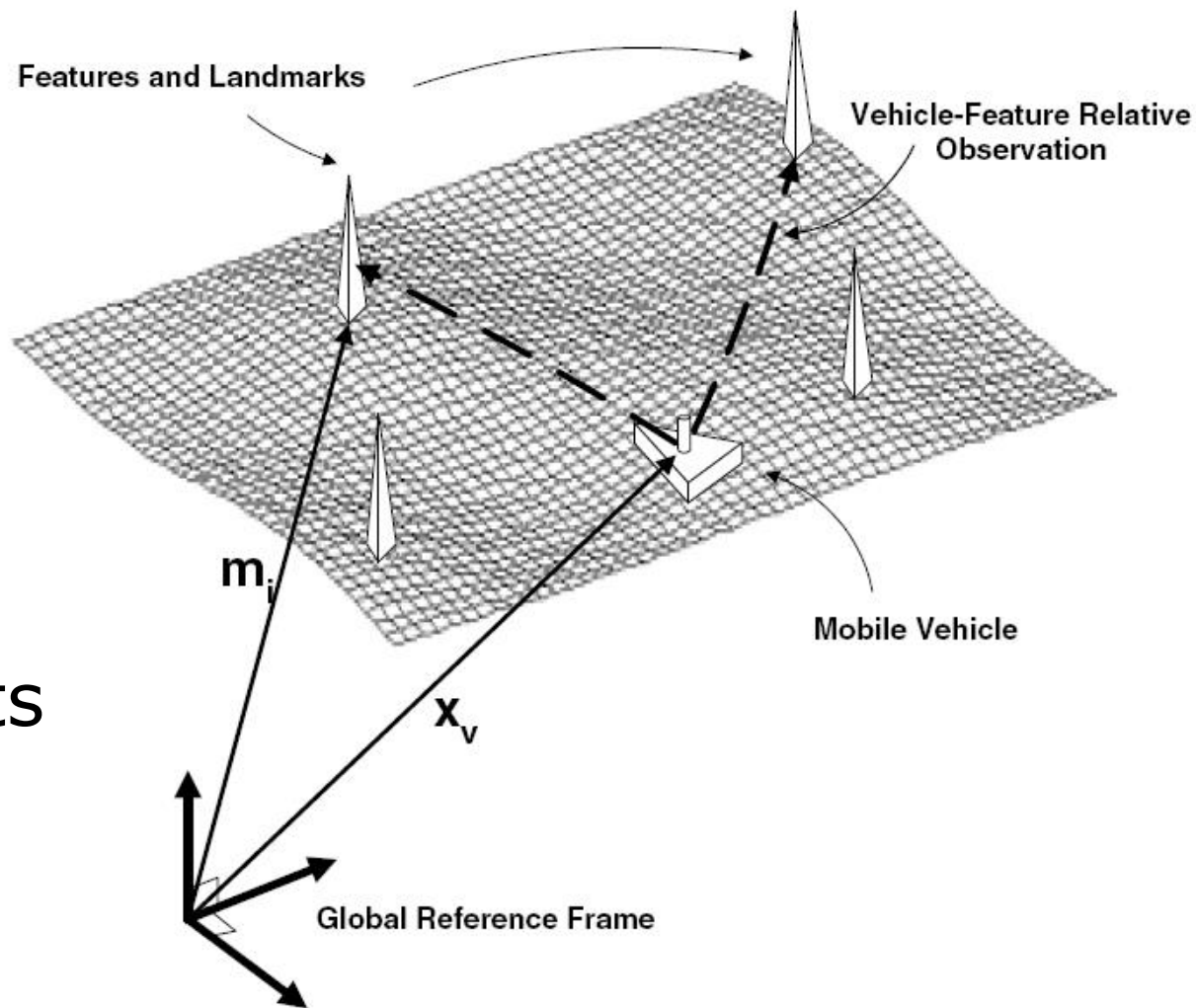
- Path of the robot

$$X_{1:k} = \{x_1, x_2, \dots, x_k\}$$



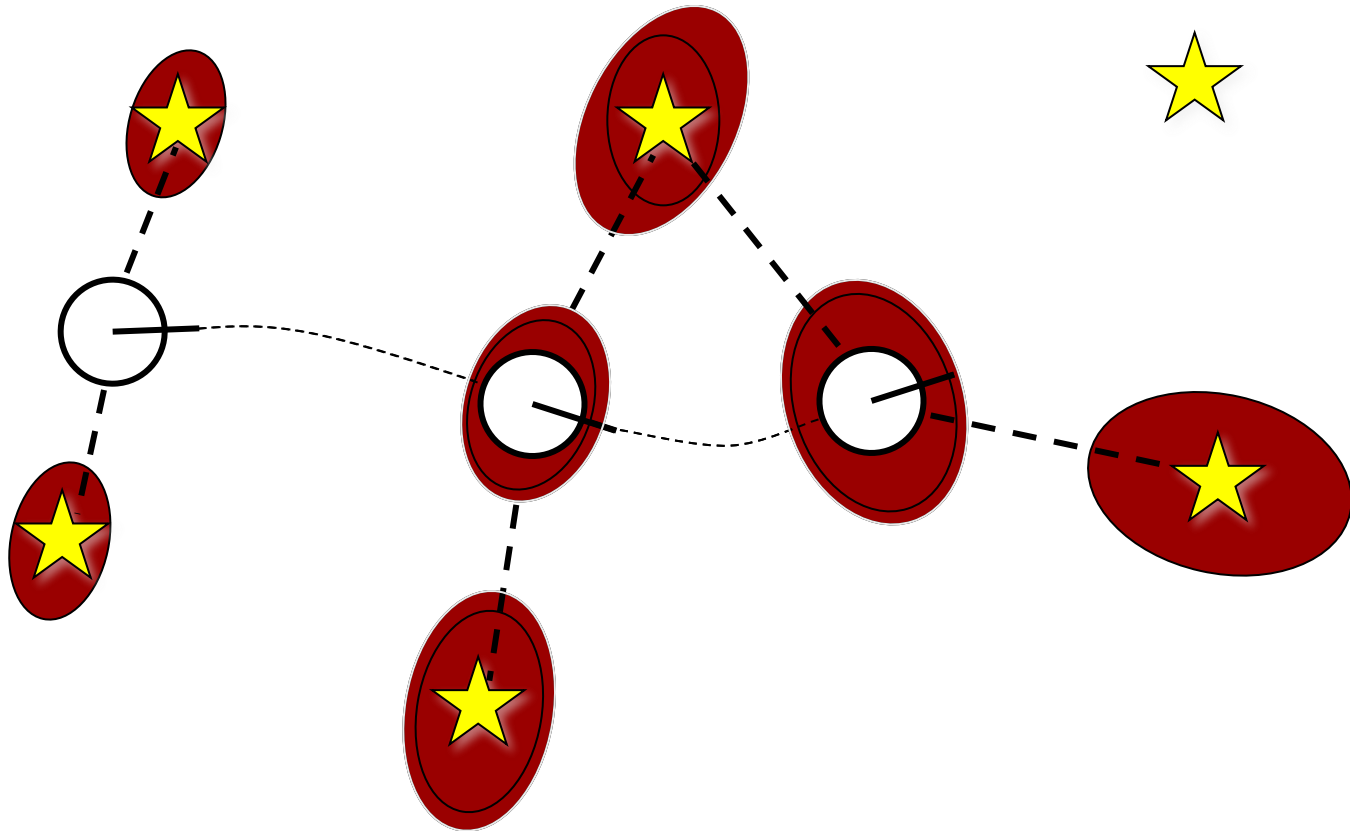
Feature-Based SLAM

- **Absolute** robot poses
- **Absolute** landmark positions
- But only **relative** measurements of landmarks



Why is SLAM a Hard Problem?

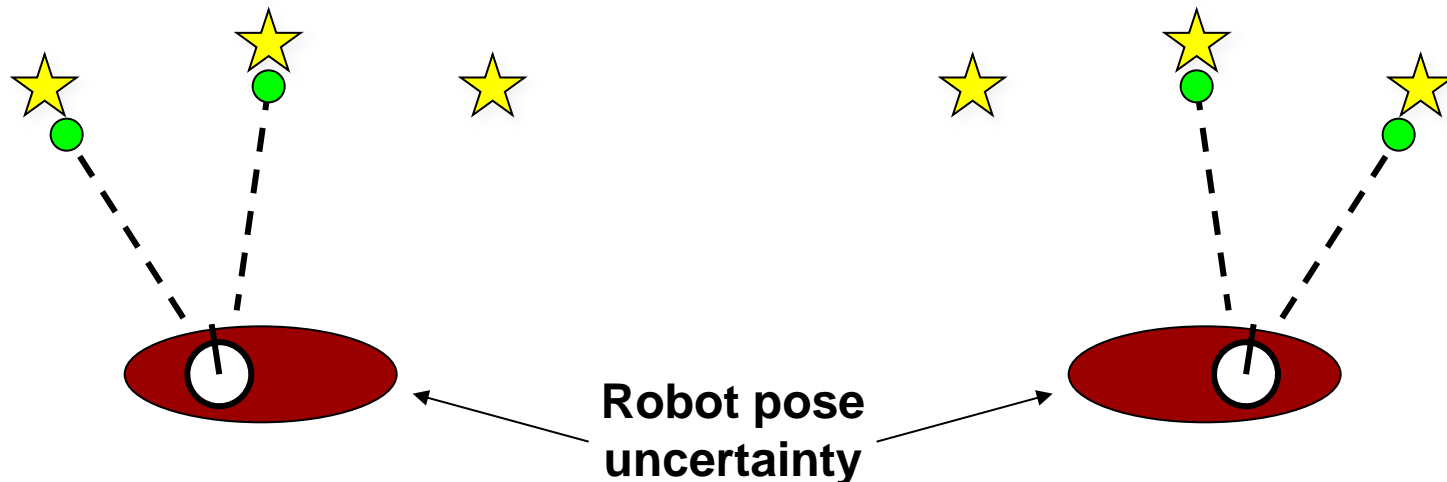
1. Robot path and map are both **unknown**



2. Errors in map and pose estimates correlated

Why is SLAM a Hard Problem?

- The **mapping between observations and landmarks is unknown**
- Picking **wrong** data associations can have **catastrophic** consequences (divergence)



SLAM: Simultaneous Localization And Mapping

- Full SLAM:

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

Estimates entire path and map!

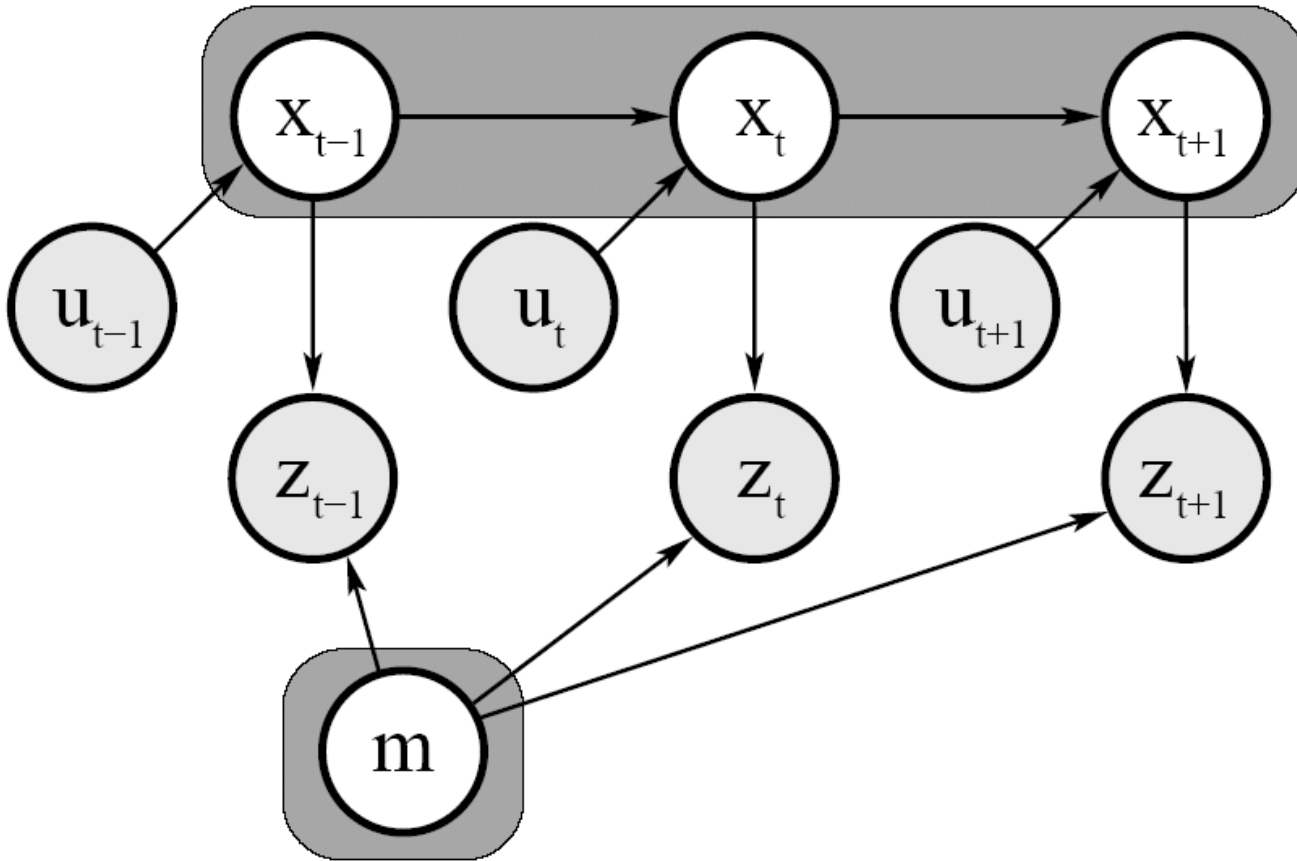
- Online SLAM:

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

Estimates most recent pose and map!

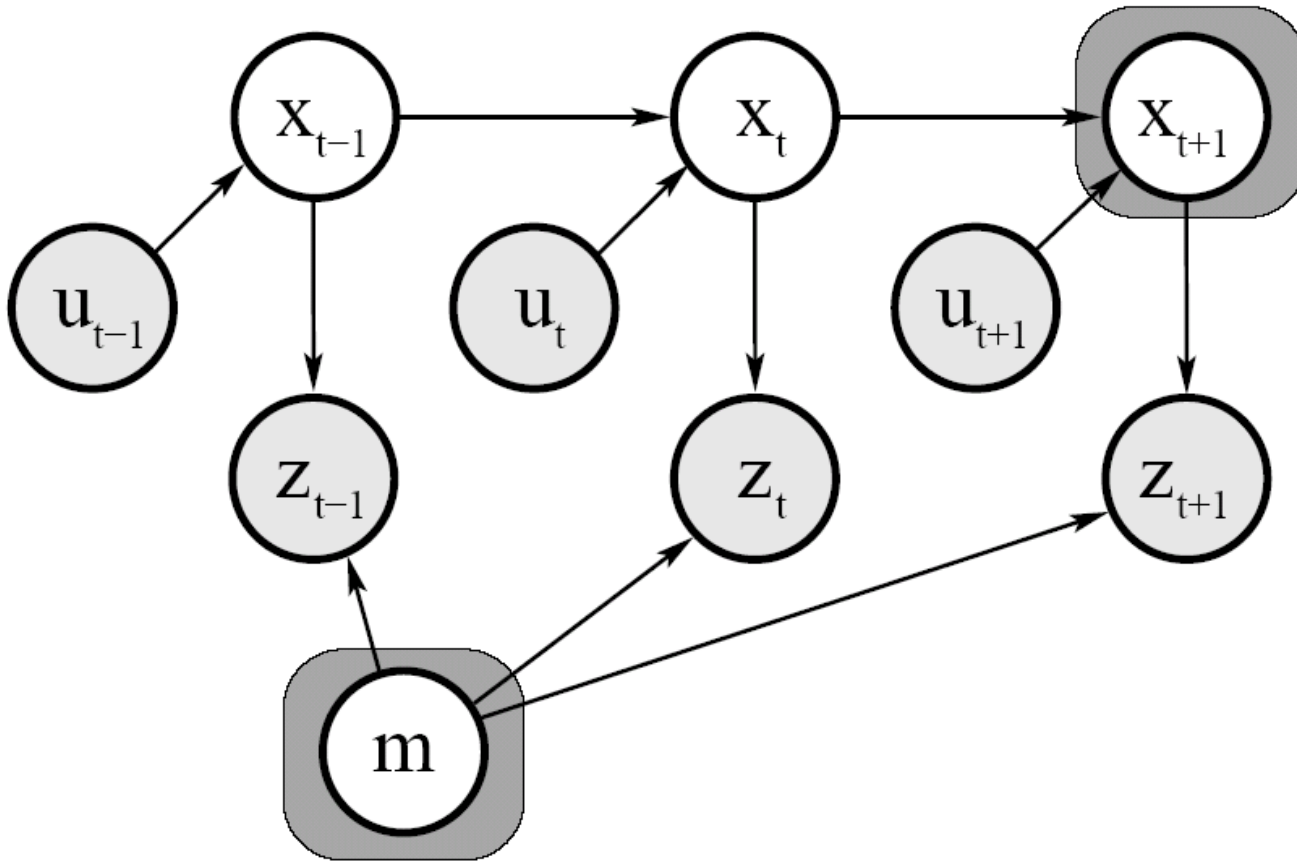
- Integrations (marginalization) typically done recursively, one at a time

Graphical Model of Full SLAM



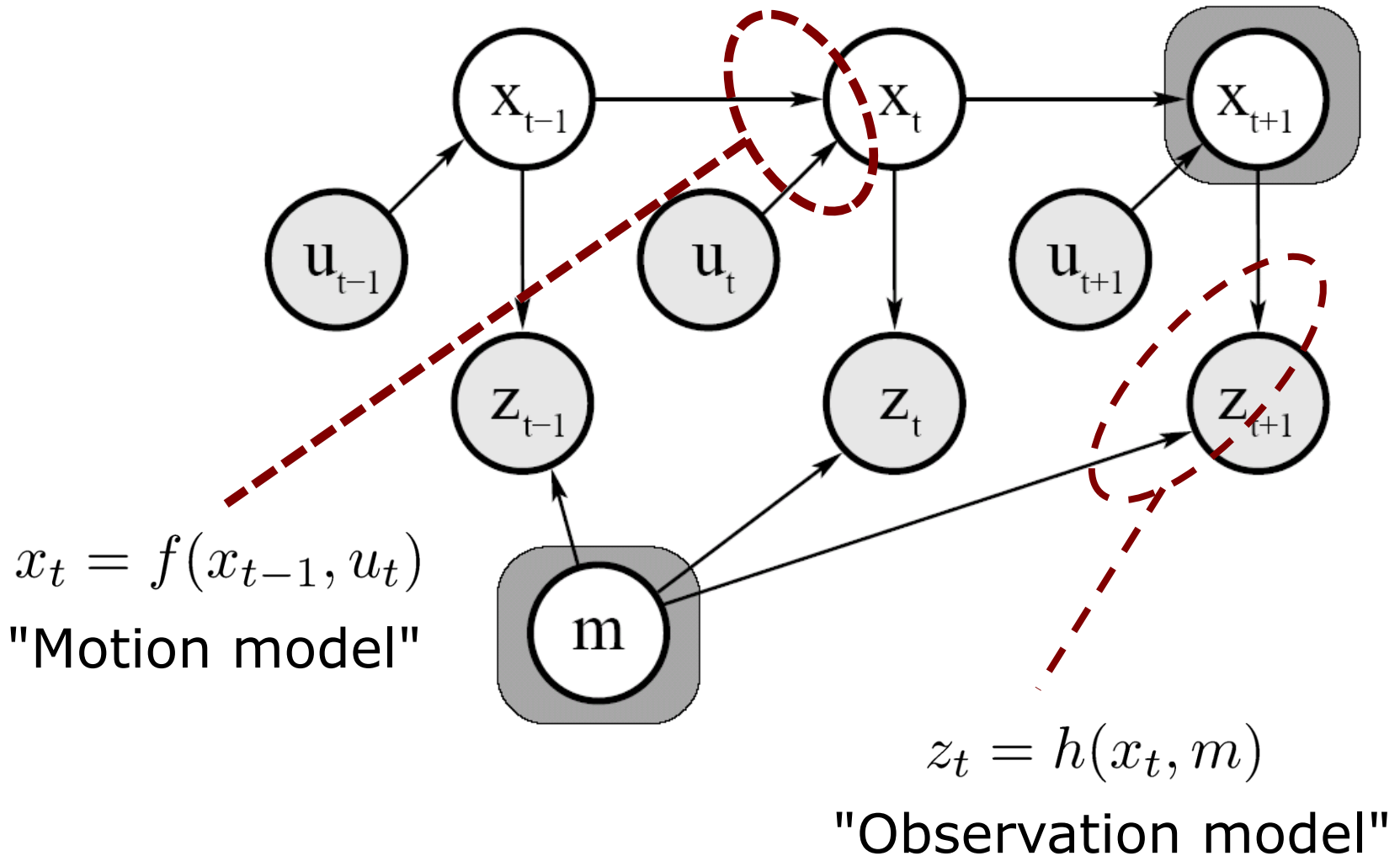
$$p(x_{1:t+1}, m \mid z_{1:t+1}, u_{1:t+1})$$

Graphical Model of Online SLAM



$$p(x_{t+1}, m \mid z_{1:t+1}, u_{1:t+1}) = \int \int \dots \int p(x_{1:t+1}, m \mid z_{1:t+1}, u_{1:t+1}) dx_1 dx_2 \dots dx_t$$

Motion and Observation Model



Remember the KF Algorithm

1. Algorithm **Kalman_filter**($\mu_{t-1}, \Sigma_{t-1}, u_t, z_t$):

2. Prediction:

3.
$$\bar{\mu}_t = A_t \mu_{t-1} + B_t u_t$$

4.
$$\bar{\Sigma}_t = A_t \Sigma_{t-1} A_t^T + R_t$$

5. Correction:

6.
$$K_t = \bar{\Sigma}_t C_t^T (C_t \bar{\Sigma}_t C_t^T + Q_t)^{-1}$$

7.
$$\mu_t = \bar{\mu}_t + K_t (z_t - C_t \bar{\mu}_t)$$

8.
$$\Sigma_t = (I - K_t C_t) \bar{\Sigma}_t$$

9. Return μ_t, Σ_t

EKF SLAM: State representation

- **Localization**

3x1 pose vector

3x3 cov. matrix

$$\mathbf{x}_k = \begin{bmatrix} x_k \\ y_k \\ \theta_k \end{bmatrix} \quad \Sigma_k = \begin{bmatrix} \sigma_x^2 & \sigma_{xy}^2 & \sigma_{x\theta}^2 \\ \sigma_{yx}^2 & \sigma_y^2 & \sigma_{y\theta}^2 \\ \sigma_{\theta x}^2 & \sigma_{\theta y}^2 & \sigma_\theta^2 \end{bmatrix}$$

- **SLAM**

Landmarks **simply extend** the state.

Growing state vector and covariance matrix!

$$\mathbf{x}_k = \begin{bmatrix} \mathbf{x}_R \\ \mathbf{m}_1 \\ \mathbf{m}_2 \\ \vdots \\ \mathbf{m}_n \end{bmatrix} \quad \Sigma_k = \begin{bmatrix} \Sigma_R & \Sigma_{RM_1} & \Sigma_{RM_2} & \cdots & \Sigma_{RM_n} \\ \Sigma_{M_1 R} & \Sigma_{M_1} & \Sigma_{M_1 M_2} & \cdots & \Sigma_{M_1 M_n} \\ \Sigma_{M_2 R} & \Sigma_{M_2 M_1} & \Sigma_{M_2} & \cdots & \Sigma_{M_2 M_n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \Sigma_{M_n R} & \Sigma_{M_n M_1} & \Sigma_{M_n M_2} & \cdots & \Sigma_{M_n} \end{bmatrix}$$

EKF SLAM: State representation

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

| | | | | | | | | |
|------------------------------------|---------------------------------------|---------------------|-------------------------|---------------------------|---------------------------|----------|---------------------------|---------------------------|
| x | σ_{xx} | σ_{xy} | $\sigma_{x\theta}$ | $\sigma_{xm_{1,x}}$ | $\sigma_{xm_{1,y}}$ | \dots | $\sigma_{xm_{n,x}}$ | $\sigma_{xm_{n,y}}$ |
| | σ_{yx} | σ_{yy} | $\sigma_{y\theta}$ | $\sigma_{ym_{1,x}}$ | $\sigma_{ym_{1,y}}$ | \dots | $\sigma_{m_{n,x}}$ | $\sigma_{m_{n,y}}$ |
| | $\sigma_{\theta x}$ | $\sigma_{\theta y}$ | $\sigma_{\theta\theta}$ | $\sigma_{\theta m_{1,x}}$ | $\sigma_{\theta m_{1,y}}$ | \dots | $\sigma_{\theta m_{n,x}}$ | $\sigma_{\theta m_{n,y}}$ |
| $m_{1,x}$ | $\sigma_{m_{1,x}x}$ | $\sigma_{m_{1,x}y}$ | σ_{θ} | $\sigma_{m_{1,x}m_{1,x}}$ | $\sigma_{m_{1,x}m_{1,y}}$ | \dots | $\sigma_{m_{1,x}m_{n,x}}$ | $\sigma_{m_{1,x}m_{n,y}}$ |
| $m_{1,y}$ | $\sigma_{m_{1,y}x}$ | $\sigma_{m_{1,y}y}$ | σ_{θ} | $\sigma_{m_{1,y}m_{1,x}}$ | $\sigma_{m_{1,y}m_{1,y}}$ | \dots | $\sigma_{m_{1,y}m_{n,x}}$ | $\sigma_{m_{1,y}m_{n,y}}$ |
| \vdots | \vdots | \vdots | \vdots | \vdots | \vdots | \ddots | \vdots | \vdots |
| $m_{n,x}$ | $\sigma_{m_{n,x}x}$ | $\sigma_{m_{n,x}y}$ | σ_{θ} | $\sigma_{m_{n,x}m_{1,x}}$ | $\sigma_{m_{n,x}m_{1,y}}$ | \dots | $\sigma_{m_{n,x}m_{n,x}}$ | $\sigma_{m_{n,x}m_{n,y}}$ |
| $m_{n,y}$ | $\sigma_{m_{n,y}x}$ | $\sigma_{m_{n,y}y}$ | σ_{θ} | $\sigma_{m_{n,y}m_{1,x}}$ | $\sigma_{m_{n,y}m_{1,y}}$ | \dots | $\sigma_{m_{n,y}m_{n,x}}$ | $\sigma_{m_{n,y}m_{n,y}}$ |
| $\underbrace{\hspace{10em}}_{\mu}$ | $\underbrace{\hspace{10em}}_{\Sigma}$ | | | | | | | |

- Can handle hundreds of dimensions

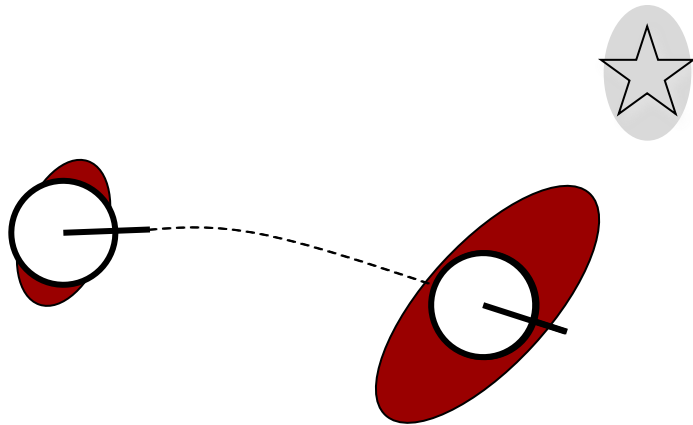
EKF SLAM: Filter Cycle

1. State prediction (odometry)
2. Measurement prediction
3. Measurement
4. Data association
5. Update
6. Integration of new landmarks

EKF SLAM: Filter Cycle

1. State prediction (odometry)
2. Measurement prediction
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6. Integration of new landmarks

EKF SLAM: State Prediction



Odometry:

$$\hat{\mathbf{x}}_R = f(\mathbf{x}_R, \mathbf{u})$$

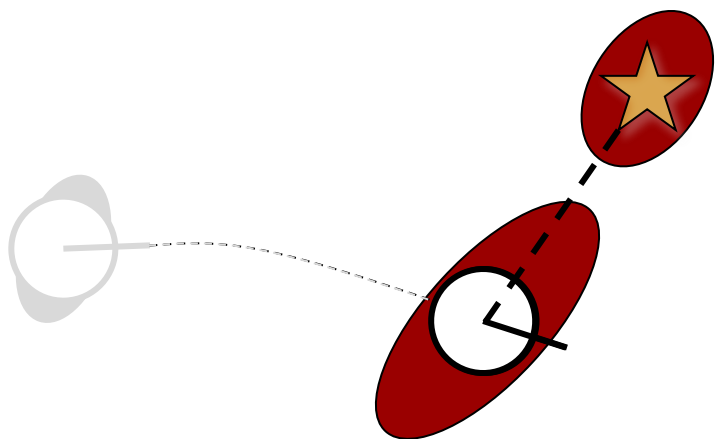
$$\hat{\Sigma}_R = F_x \Sigma_R F_x^T + F_u U F_u^T$$

Robot-landmark cross-covariance prediction:

$$\hat{\Sigma}_{RM_i} = F_x \Sigma_{RM_i}$$

$$\underbrace{\begin{bmatrix} \mathbf{x}_R \\ \mathbf{m}_1 \\ \vdots \\ \mathbf{m}_n \end{bmatrix}}_{\mu} \quad \underbrace{\begin{bmatrix} \Sigma_R & \Sigma_{RM_1} & \dots & \Sigma_{RM_n} \\ \Sigma_{M_1 R} & \Sigma_{M_1} & \dots & \Sigma_{M_1 M_n} \\ \vdots & \vdots & \ddots & \vdots \\ \Sigma_{M_n R} & \Sigma_{M_n M_1} & \dots & \Sigma_{M_n} \end{bmatrix}}_{\Sigma}$$

EKF SLAM: Measurement Prediction



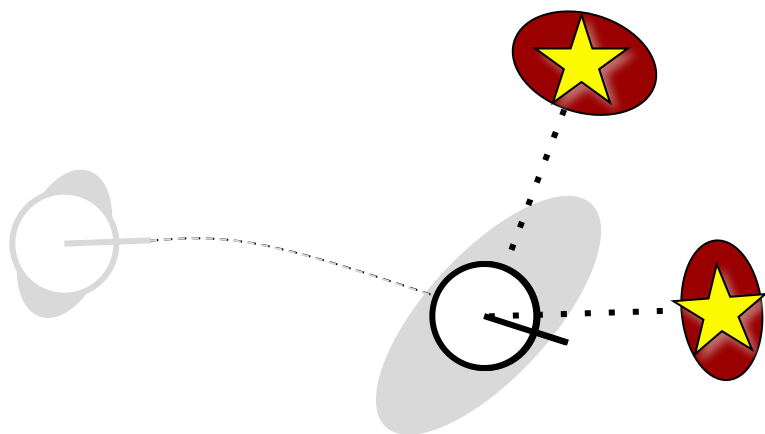
Global-to-local
frame transform h

$$\hat{\mathbf{z}}_k = h(\hat{\mathbf{x}}_k)$$

$$\underbrace{\begin{bmatrix} \mathbf{x}_R \\ \mathbf{m}_1 \\ \vdots \\ \mathbf{m}_n \end{bmatrix}}_{\mu} \quad \underbrace{\begin{bmatrix} \Sigma_R & \Sigma_{RM_1} & \dots & \Sigma_{RM_n} \\ \Sigma_{M_1 R} & \Sigma_{M_1} & \dots & \Sigma_{M_1 M_n} \\ \vdots & \vdots & \ddots & \vdots \\ \Sigma_{M_n R} & \Sigma_{M_n M_1} & \dots & \Sigma_{M_n} \end{bmatrix}}_{\Sigma}$$

EKF SLAM: Obtained Measurement

(x,y) -point landmarks



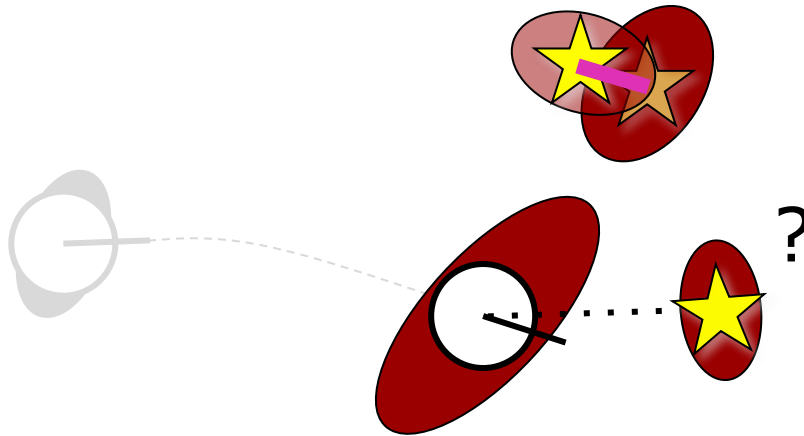
$$\mathbf{z}_k = \begin{bmatrix} x_1 \\ y_1 \\ x_2 \\ y_2 \end{bmatrix} = \begin{bmatrix} \mathbf{z}_1 \\ \mathbf{z}_2 \end{bmatrix}$$

$$R_k = \begin{bmatrix} R_1 & 0 \\ 0 & R_2 \end{bmatrix}$$

$$\underbrace{\begin{bmatrix} \mathbf{x}_R \\ \mathbf{m}_1 \\ \vdots \\ \mathbf{m}_n \end{bmatrix}}_{\mu}$$

$$\underbrace{\begin{bmatrix} \Sigma_R & \Sigma_{RM_1} & \dots & \Sigma_{RM_n} \\ \Sigma_{M_1 R} & \Sigma_{M_1} & \dots & \Sigma_{M_1 M_n} \\ \vdots & \vdots & \ddots & \vdots \\ \Sigma_{M_n R} & \Sigma_{M_n M_1} & \dots & \Sigma_{M_n} \end{bmatrix}}_{\Sigma}$$

EKF SLAM: Data Association



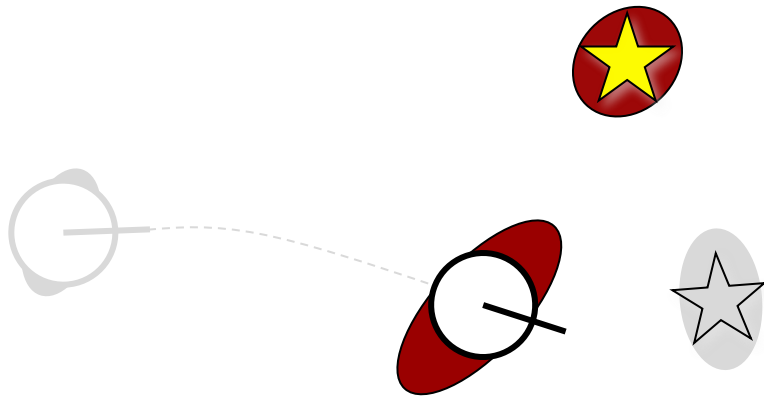
Associates predicted measurements $\hat{\mathbf{z}}_k^i$ with observation \mathbf{z}_k^j

$$\nu_k^{ij} = \mathbf{z}_k^j - \hat{\mathbf{z}}_k^i$$

$$S_k^{ij} = R_k^j + H^i \hat{\Sigma}_k H^{iT}$$

$$\underbrace{\begin{bmatrix} \mathbf{x}_R \\ \mathbf{m}_1 \\ \vdots \\ \mathbf{m}_n \end{bmatrix}}_{\mu} \quad \underbrace{\begin{bmatrix} \Sigma_R & \Sigma_{RM_1} & \dots & \Sigma_{RM_n} \\ \Sigma_{M_1 R} & \Sigma_{M_1} & \dots & \Sigma_{M_1 M_n} \\ \vdots & \vdots & \ddots & \vdots \\ \Sigma_{M_n R} & \Sigma_{M_n M_1} & \dots & \Sigma_{M_n} \end{bmatrix}}_{\Sigma}$$

EKF SLAM: Update Step



The usual Kalman filter expressions

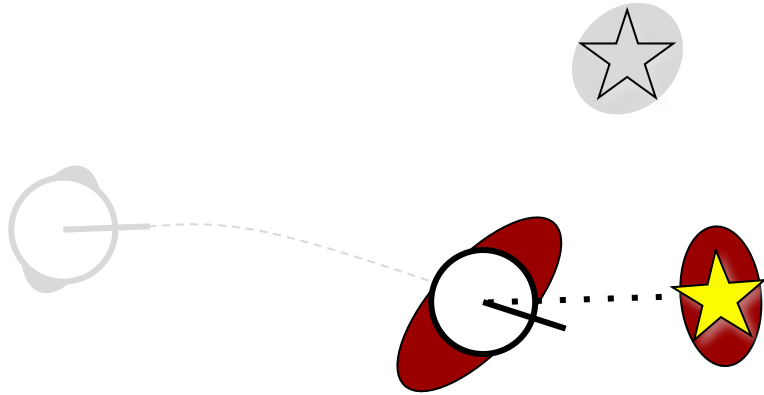
$$K_k = \hat{\Sigma}_k H^T S_k^{-1}$$

$$\mathbf{x}_k = \hat{\mathbf{x}}_k + K_k \nu_k$$

$$C_k = (I - K_k H) \hat{\Sigma}_k$$

$$\underbrace{\begin{bmatrix} \mathbf{x}_R \\ \mathbf{m}_1 \\ \vdots \\ \mathbf{m}_n \end{bmatrix}}_{\mu} \quad \underbrace{\begin{bmatrix} \Sigma_R & \Sigma_{RM_1} & \dots & \Sigma_{RM_n} \\ \Sigma_{M_1 R} & \Sigma_{M_1} & \dots & \Sigma_{M_1 M_n} \\ \vdots & \vdots & \ddots & \vdots \\ \Sigma_{M_n R} & \Sigma_{M_n M_1} & \dots & \Sigma_{M_n} \end{bmatrix}}_{\Sigma}$$

EKF SLAM: New Landmarks



State augmented by

$$\mathbf{m}_{n+1} = g(\mathbf{x}_R, \mathbf{z}_j)$$

$$\Sigma_{M_{n+1}} = G_R \Sigma_R G_R^T + G_z R_j G_z^T$$

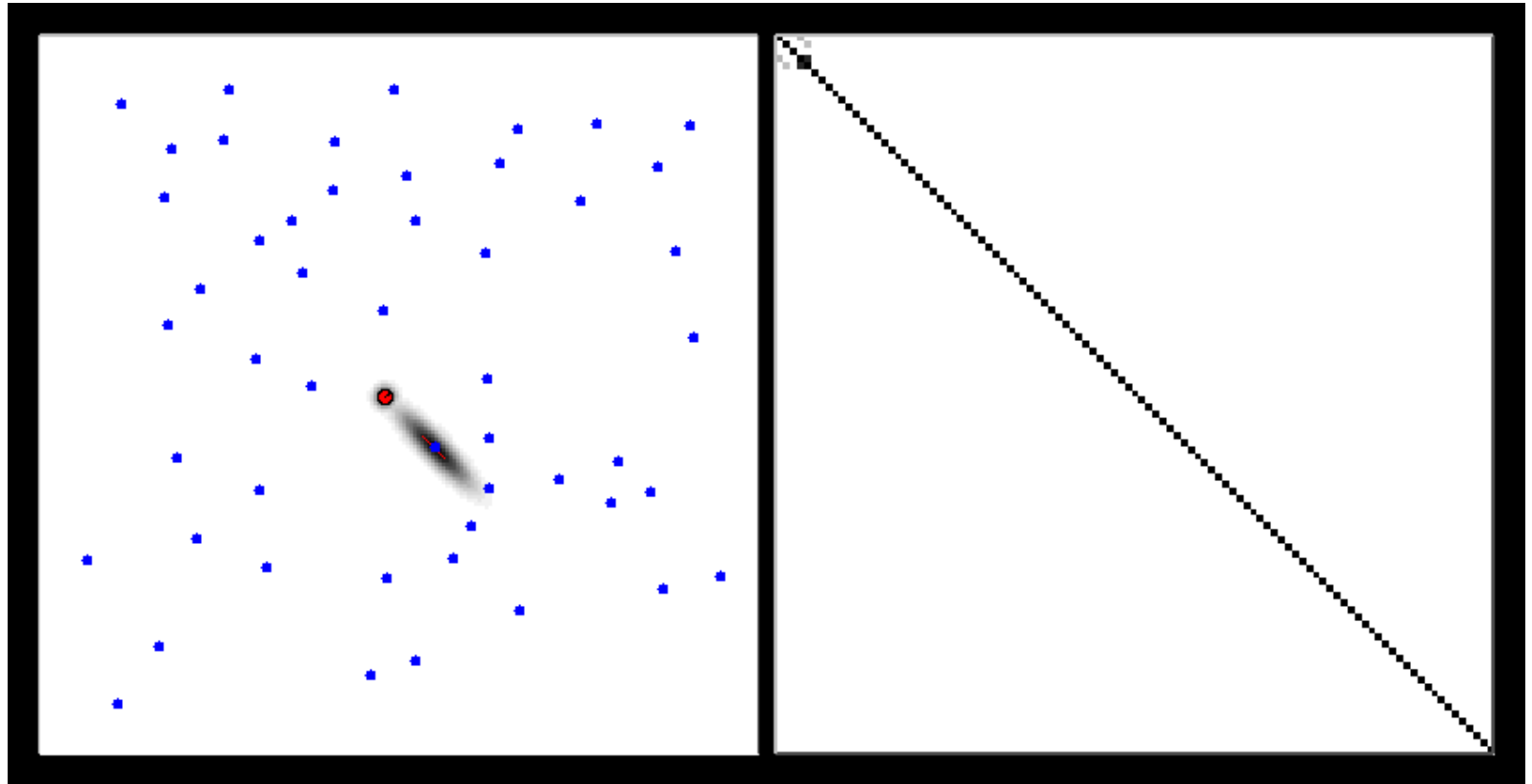
Cross-covariances:

$$\Sigma_{M_{n+1} M_i} = G_R \Sigma_{R M_i}$$

$$\Sigma_{M_{n+1} R} = G_R \Sigma_R$$

$$\underbrace{\begin{bmatrix} \mathbf{x}_R \\ \mathbf{m}_1 \\ \vdots \\ \mathbf{m}_n \\ \mathbf{m}_{n+1} \end{bmatrix}}_{\boldsymbol{\mu}} \quad \underbrace{\begin{bmatrix} \Sigma_R & \Sigma_{R M_1} & \dots & \Sigma_{R M_n} & \Sigma_{R M_{n+1}} \\ \Sigma_{M_1 R} & \Sigma_{M_1} & \dots & \Sigma_{M_1 M_n} & \Sigma_{M_1 M_{n+1}} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ \Sigma_{M_n R} & \Sigma_{M_n M_1} & \dots & \Sigma_{M_n} & \Sigma_{M_n M_{n+1}} \\ \Sigma_{M_{n+1} R} & \Sigma_{M_{n+1} M_1} & \dots & \Sigma_{M_{n+1} M_n} & \Sigma_{M_{n+1}} \end{bmatrix}}_{\boldsymbol{\Sigma}}$$

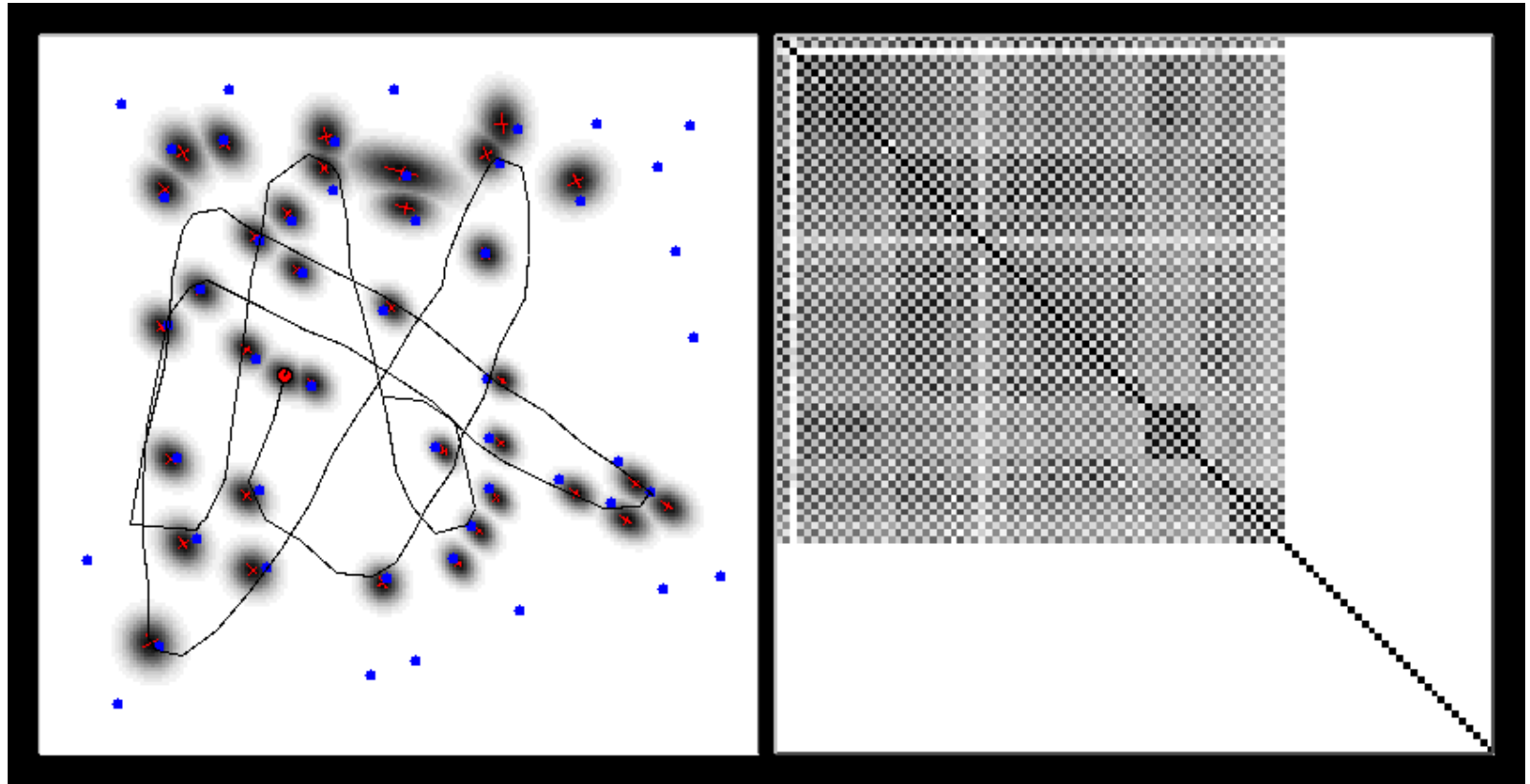
EKF SLAM



Map

Correlation matrix

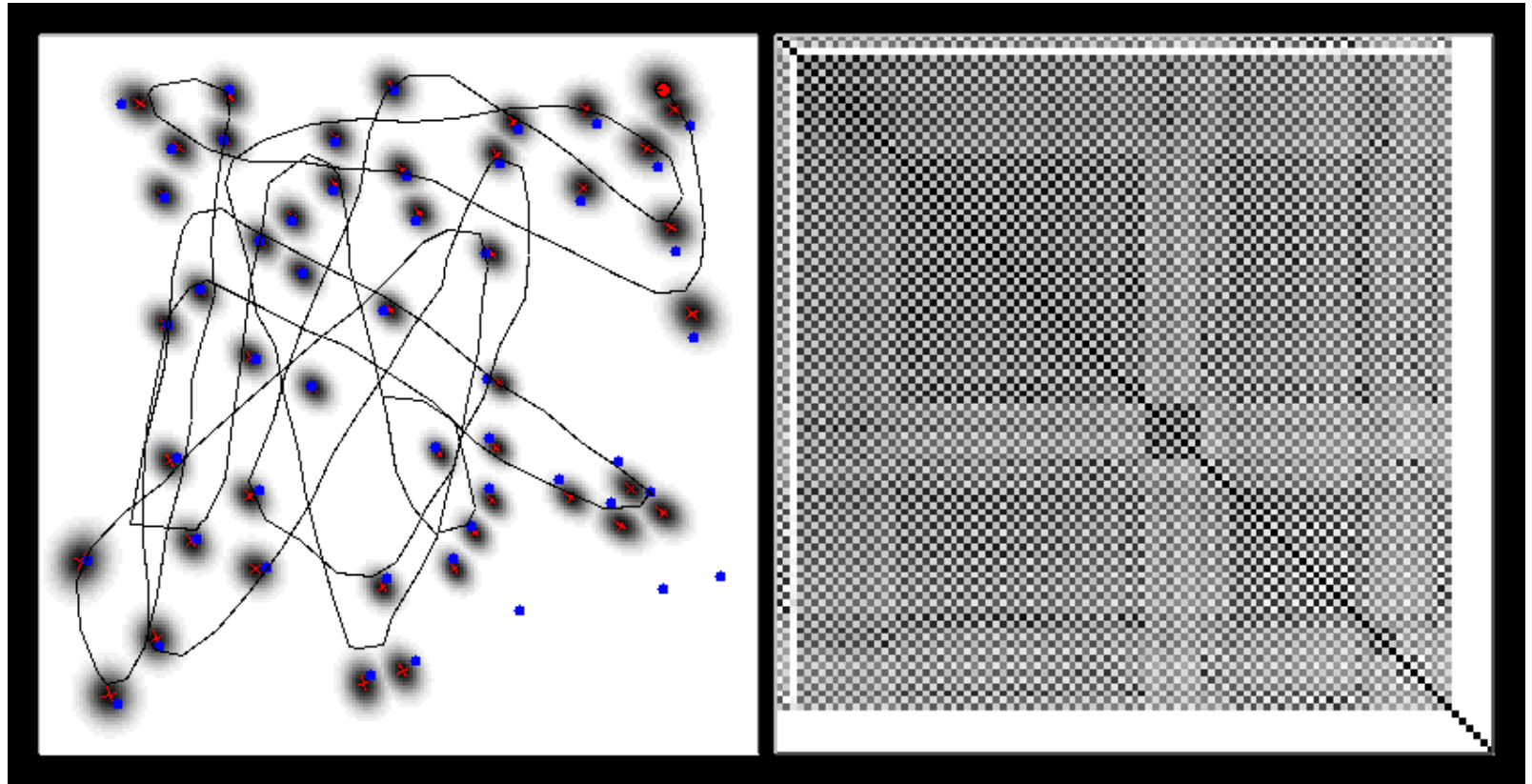
EKF SLAM



Map

Correlation matrix

EKF SLAM



Map

Correlation matrix

EKF SLAM: Correlations Matter

- What if we neglected cross-correlations?

$$\Sigma_k = \begin{bmatrix} \Sigma_R & 0 & \cdots & 0 \\ 0 & \Sigma_{M_1} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \Sigma_{M_n} \end{bmatrix} \quad \begin{aligned} \Sigma_{RM_i} &= \mathbf{0}_{3 \times 2} \\ \Sigma_{M_i M_{i+1}} &= \mathbf{0}_{2 \times 2} \end{aligned}$$

EKF SLAM: Correlations Matter

- What if we neglected cross-correlations?

$$\Sigma_k = \begin{bmatrix} \Sigma_R & 0 & \cdots & 0 \\ 0 & \Sigma_{M_1} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \Sigma_{M_n} \end{bmatrix} \quad \begin{aligned} \Sigma_{RM_i} &= \mathbf{0}_{3 \times 2} \\ \Sigma_{M_i M_{i+1}} &= \mathbf{0}_{2 \times 2} \end{aligned}$$

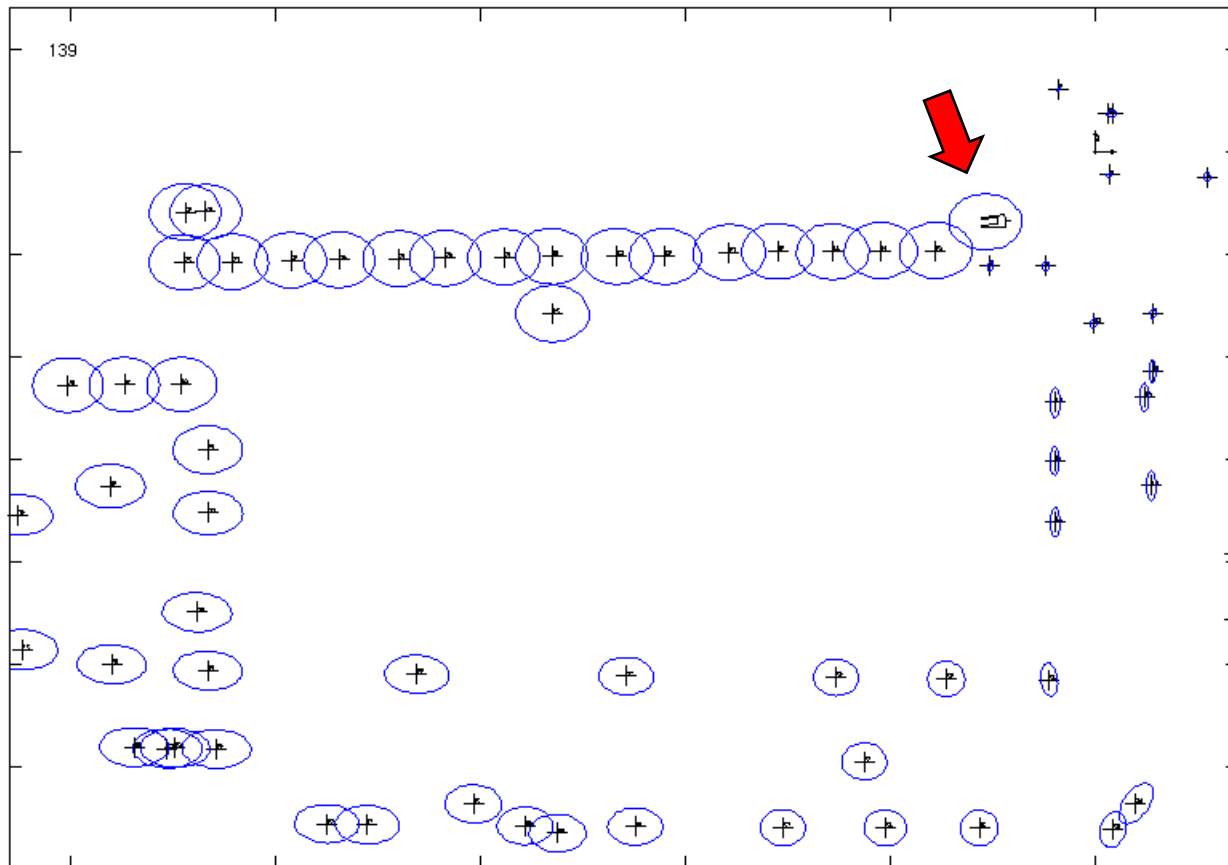
- Landmark and robot uncertainties would become overly optimistic
- Data association would fail
- Multiple map entries of the same landmark
- Inconsistent map

SLAM: Loop Closure

- **Recognizing an already mapped area**, typically after a long exploration path (the robot “closes a loop”)
- Structurally identical to data association, but
 - high levels of ambiguity
 - possibly useless validation gates
 - environment symmetries
- Uncertainties **collapse** after a loop closure (whether the closure was correct or not)

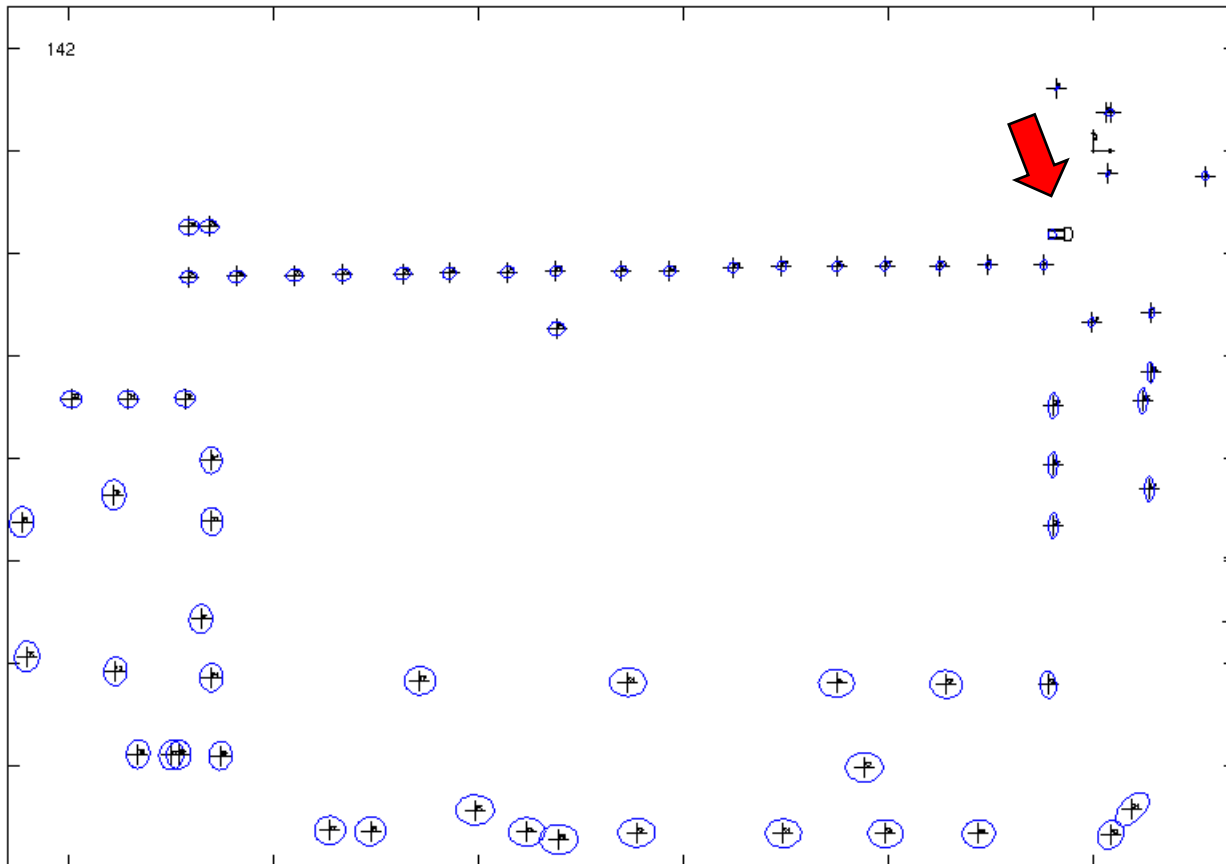
SLAM: Loop Closure

- Before loop closure



SLAM: Loop Closure

- After loop closure

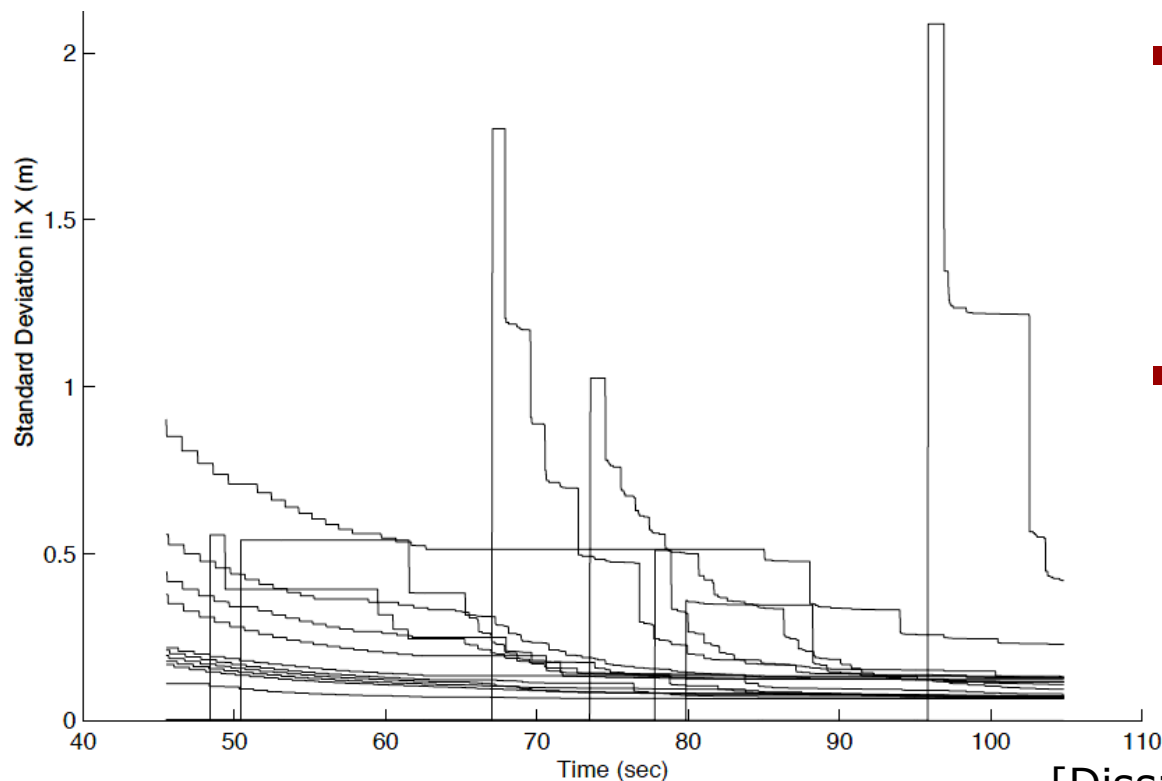


SLAM: Loop Closure

- By revisiting already mapped areas, uncertainties in robot and landmark estimates can be **reduced**
 - This can be exploited when **exploring** an environment for the sake of better (e.g. more accurate) maps
 - Exploration: the problem of ***where to acquire new information***
- See separate chapter on exploration

KF-SLAM Properties (Linear Case)

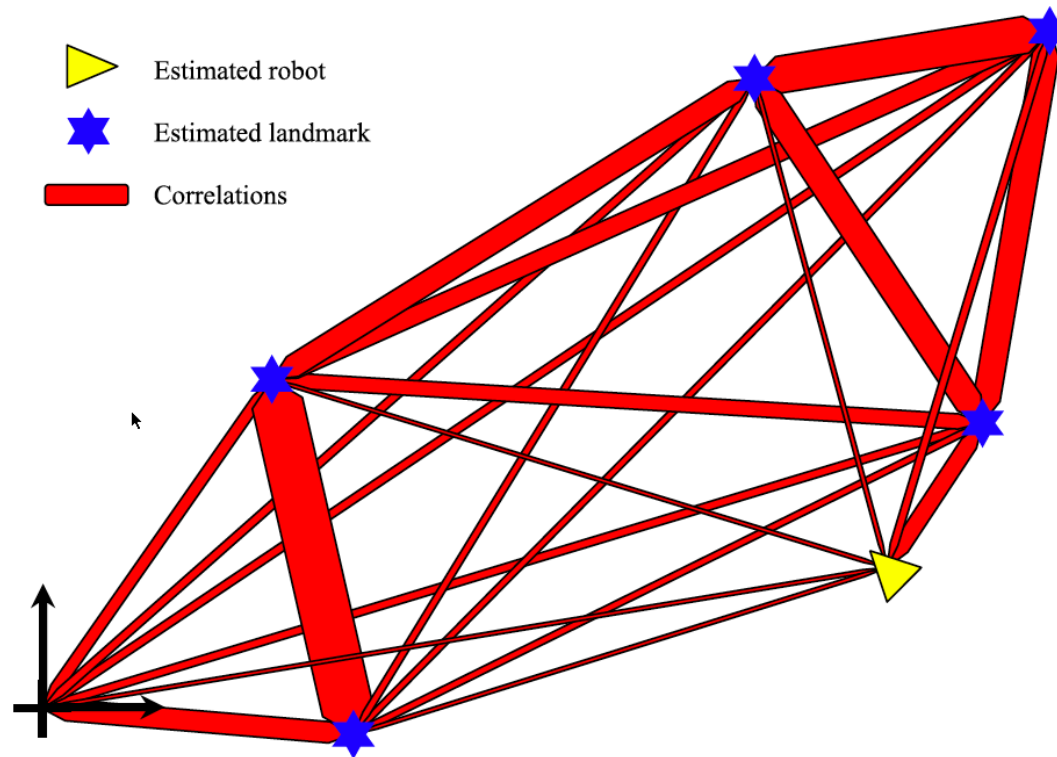
- The **determinant** of any sub-matrix of the map covariance matrix **decreases monotonically** as successive observations are made



- When a new landmark is initialized, its **uncertainty is maximal**
- Landmark uncertainty **decreases monotonically** with each new observation

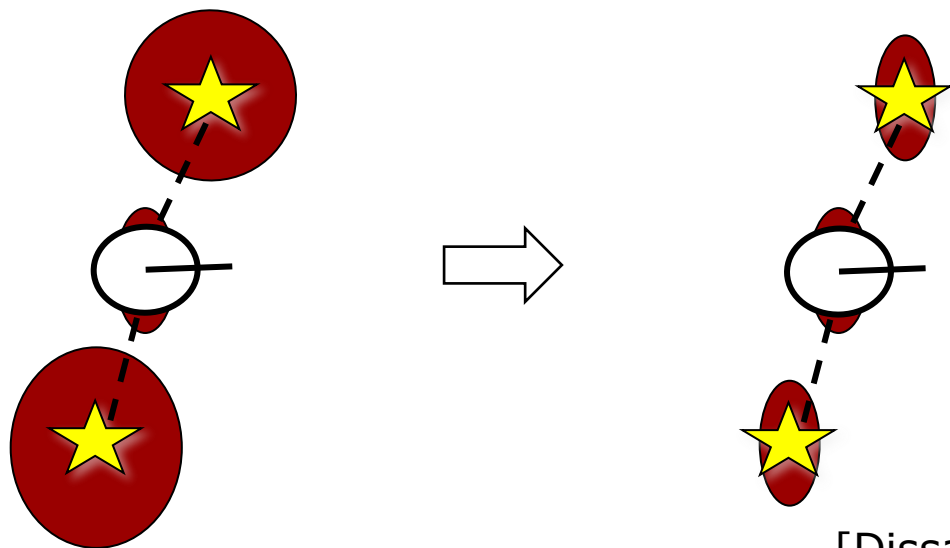
KF-SLAM Properties (Linear Case)

- In the limit, the landmark estimates become **fully correlated**



KF-SLAM Properties (Linear Case)

- In the limit, the **covariance** associated with any single landmark location estimate is determined only by the **initial covariance** in the vehicle location estimate.



EKF SLAM Example: Victoria Park Dataset

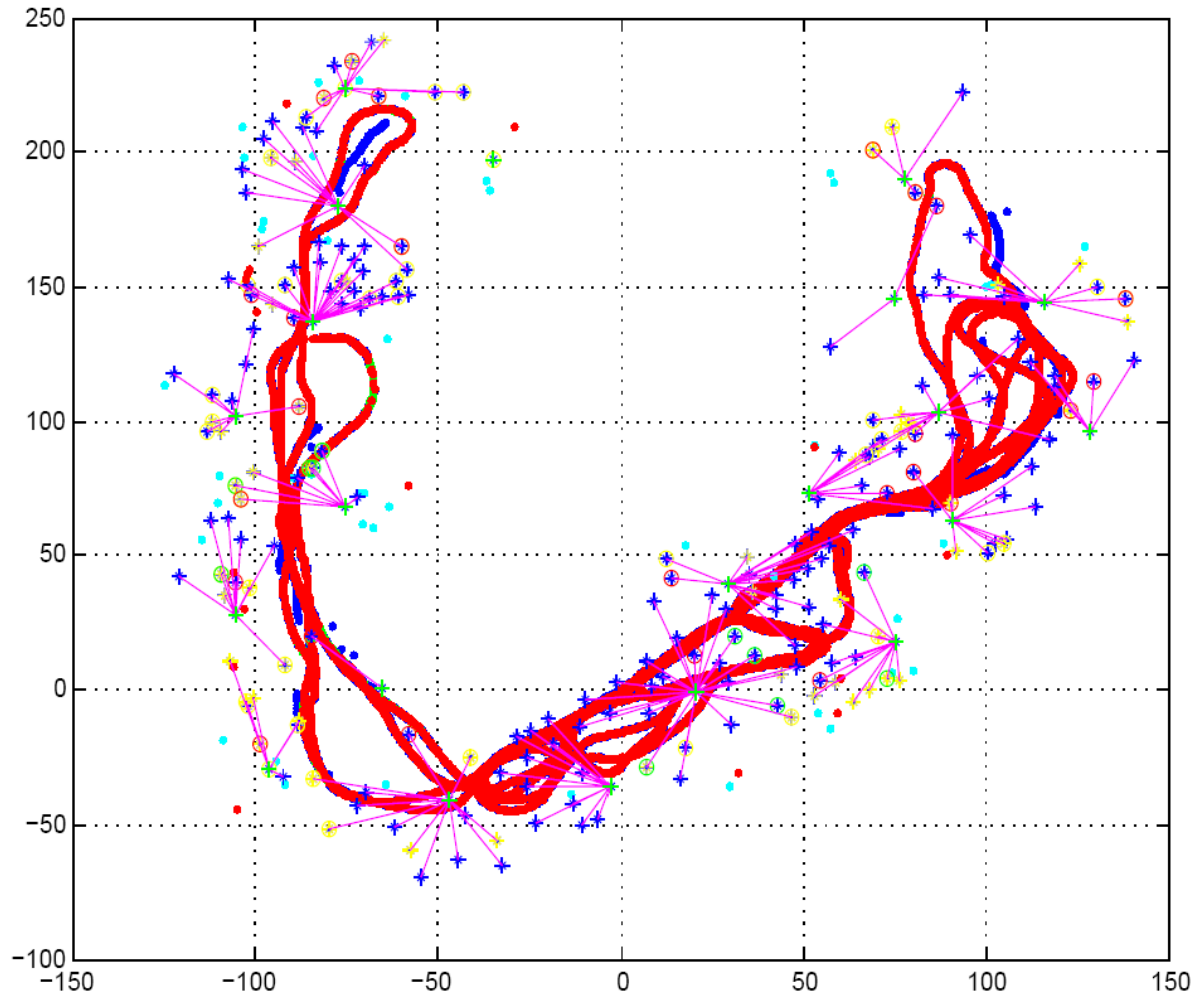


Victoria Park: Data Acquisition



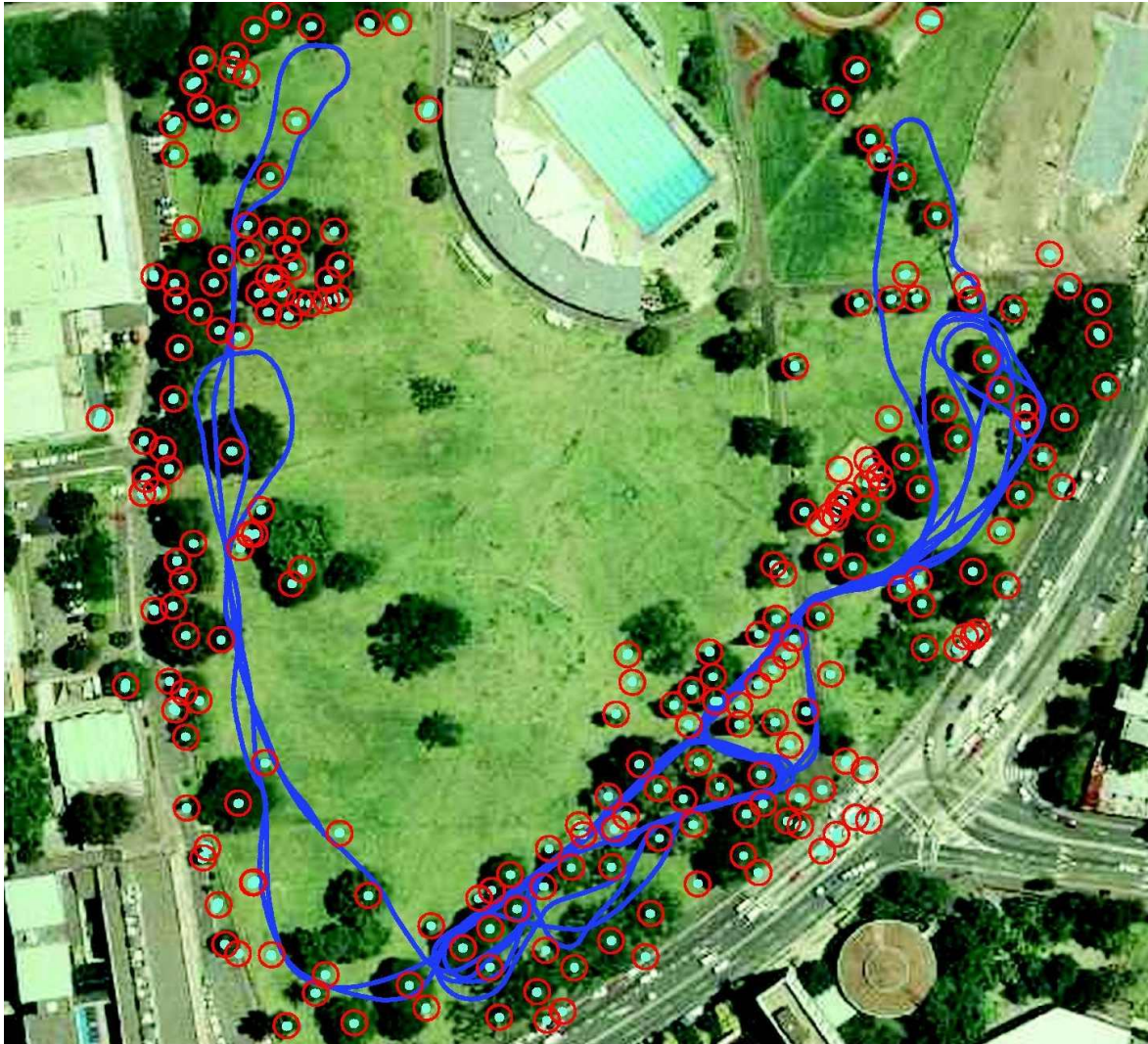
[courtesy by E. Nebot]

Victoria Park: Estimated Trajectory



[courtesy by E. Nebot]

Victoria Park: Landmarks



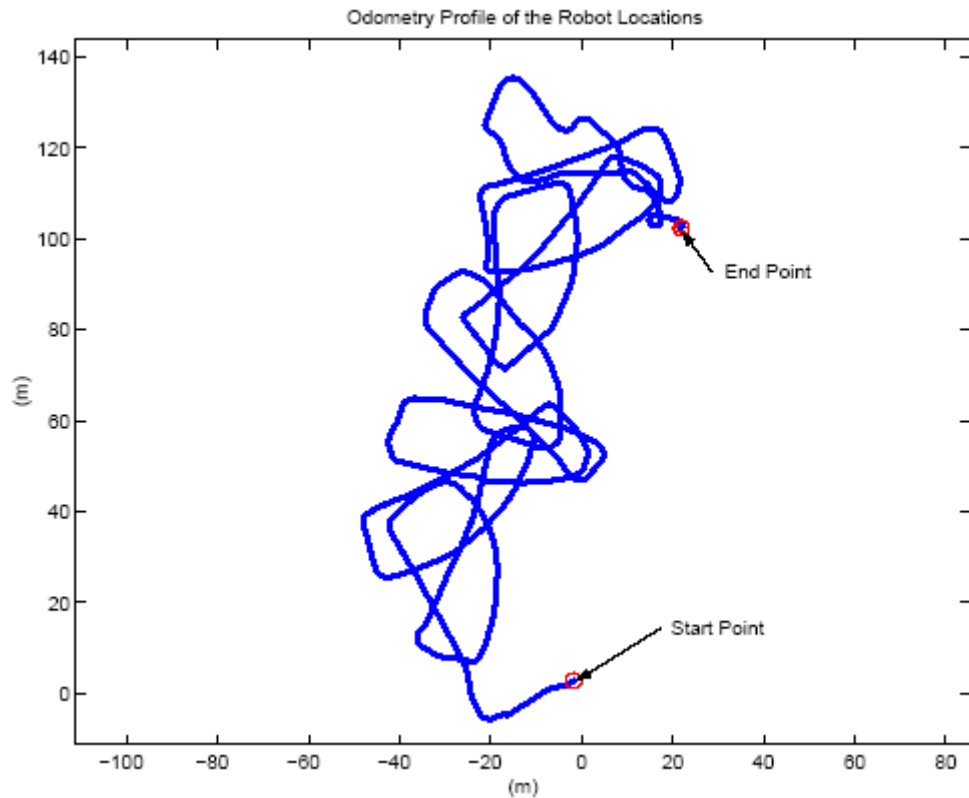
[courtesy by E. Nebot]

EKF SLAM Example: Tennis Court

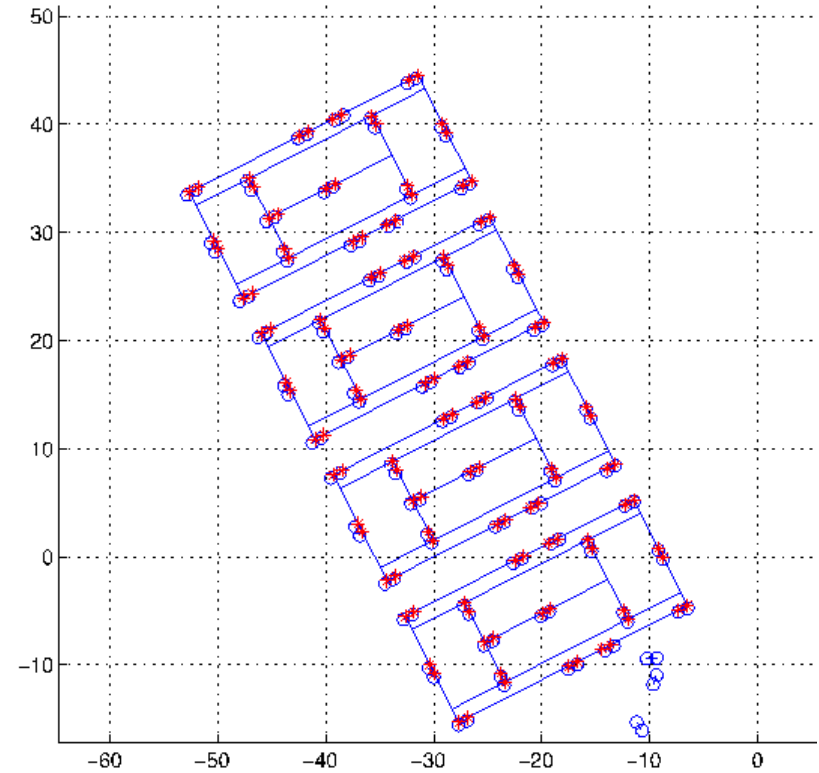


[courtesy by J. Leonard]

EKF SLAM Example: Tennis Court



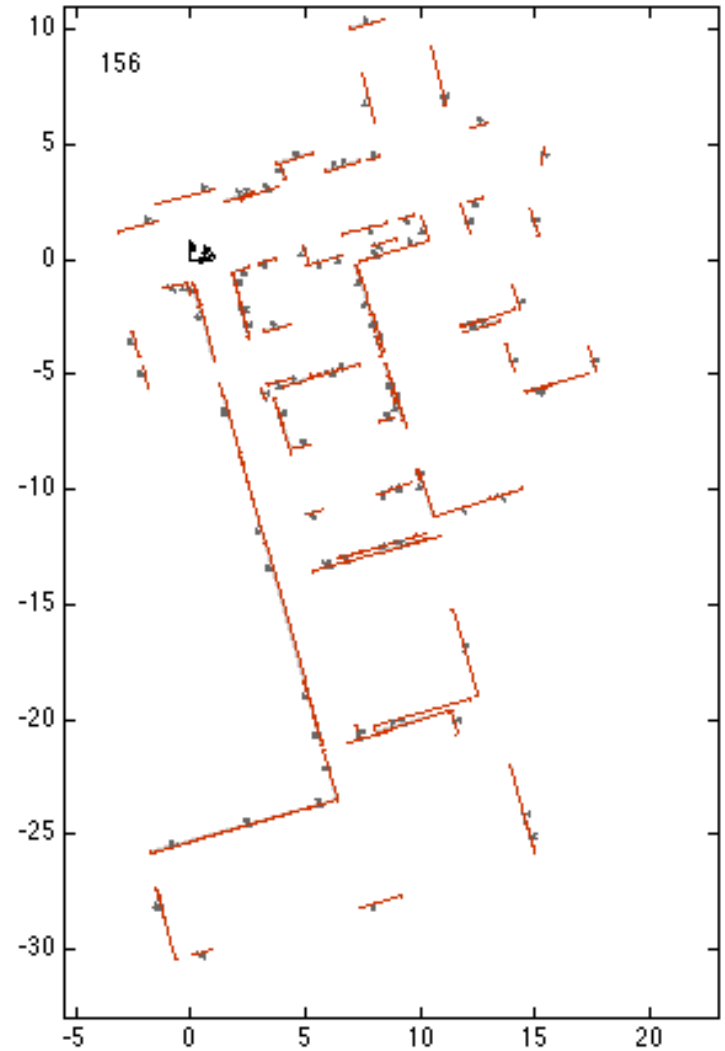
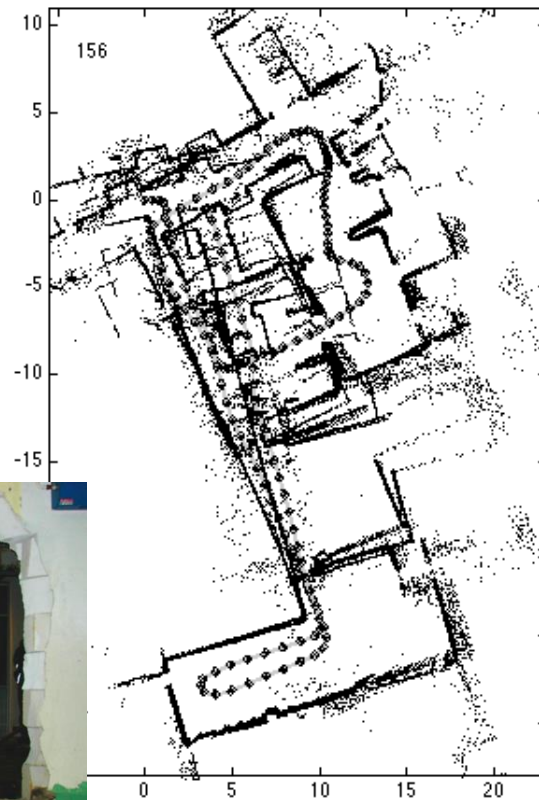
odometry



estimated trajectory

EKF SLAM Example: Line Features

- KTH Bakery Data Set



EKF-SLAM: Complexity

- Cost per step: quadratic in n , the number of landmarks: $O(n^2)$
- Total cost to build a map with n landmarks: $O(n^3)$
- Memory consumption: $O(n^2)$
- Problem: becomes computationally intractable for large maps!
- There exists variants to circumvent these problems

SLAM Techniques

- EKF SLAM
- FastSLAM
- Graph-based SLAM
- Topological SLAM
(mainly place recognition)
- Scan Matching / Visual Odometry
(only locally consistent maps)
- Approximations for SLAM: Local submaps, Sparse extended information filters, Sparse links, Thin junction tree filters, etc.
- ...

EKF-SLAM: Summary

- The first SLAM solution
- Convergence proof for linear Gaussian case
- Can diverge if nonlinearities are large (and the real world is nonlinear ...)
- Can deal only with a single mode
- Successful in medium-scale scenes
- Approximations exist to reduce the computational complexity