Disclaimer

These slides are intended as presentation aids for the lecture. They contain information that would otherwise be to difficult or time-consuming to reproduce on the board. But they are incomplete, not self-explanatory, and are not always used in the order they appear in this presentation. As a result, these slides should not be used as a script for this course. I recommend you take notes during class, maybe on the slides themselves. It has been shown that taking notes improves learning success.

Reading for this set of slides

- Planning Algorithms (Steve LaValle)
  - 6 Combinatorial Motion Planning (6.1 – 6.3)
  - 8 Feedback Motion Planning (8.1, 8.2)
- Please refer to the slides for potential fields and vehicle kinematics

Please note that this set of slides is intended as support for the lecture, not as a stand-alone script. If you want to study for this course, please use these slides in conjunction with the indicated chapters in the text books. The textbooks are available online or in the TUB library (many copies that can be checked out for the entire semester. There are also some aspects of the lectures that will not be covered in the text books but can still be part of the homework or exam. For those It is important that you attend class or ask somebody about what was covered in class.

Robotics

Simultaneous Localization and Mapping (SLAM)

TU Berlin
Oliver Brock

The SLAM Problem

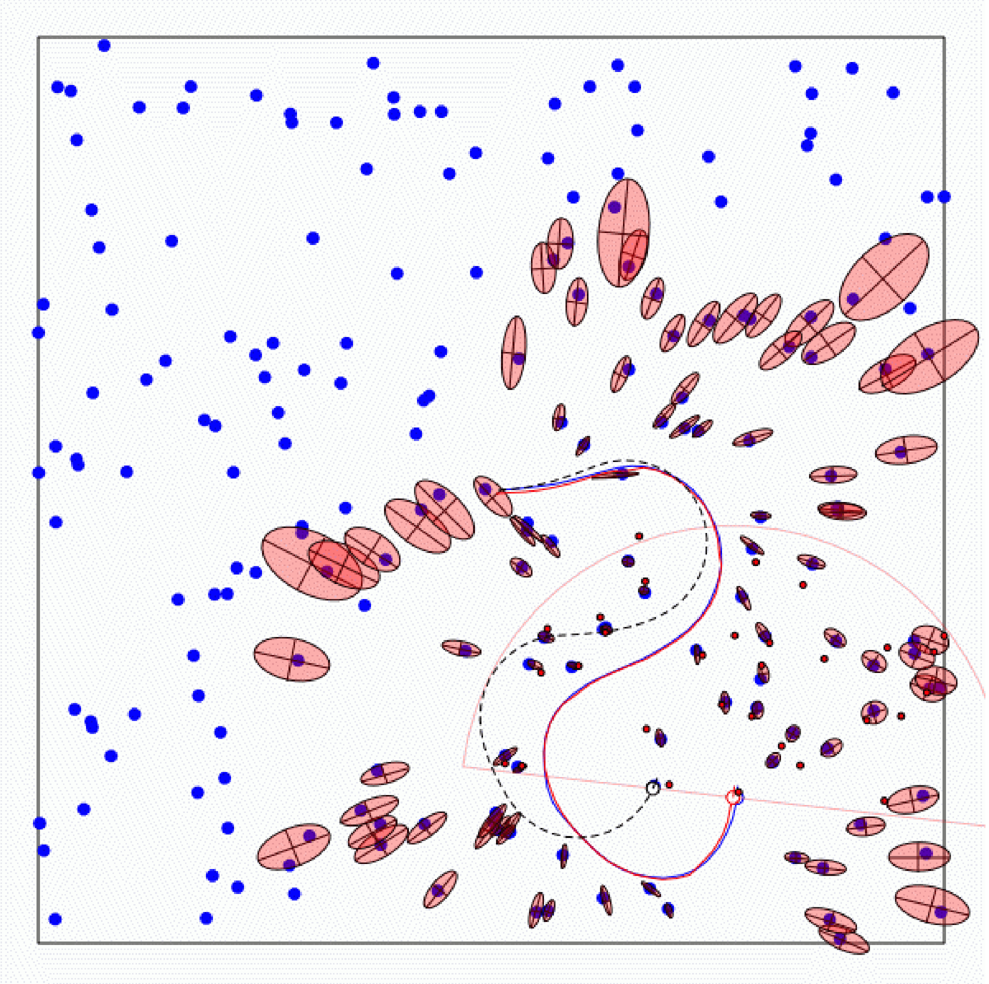
A robot moving though an unknown, static environment

Given:

- The robot's controls
- Observations of nearby features

Estimate:

- Map of features
- Path of the robot



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

SLAM: Simultaneous Localization and Mapping

- Full SLAM:

Estimates entire path and map!

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

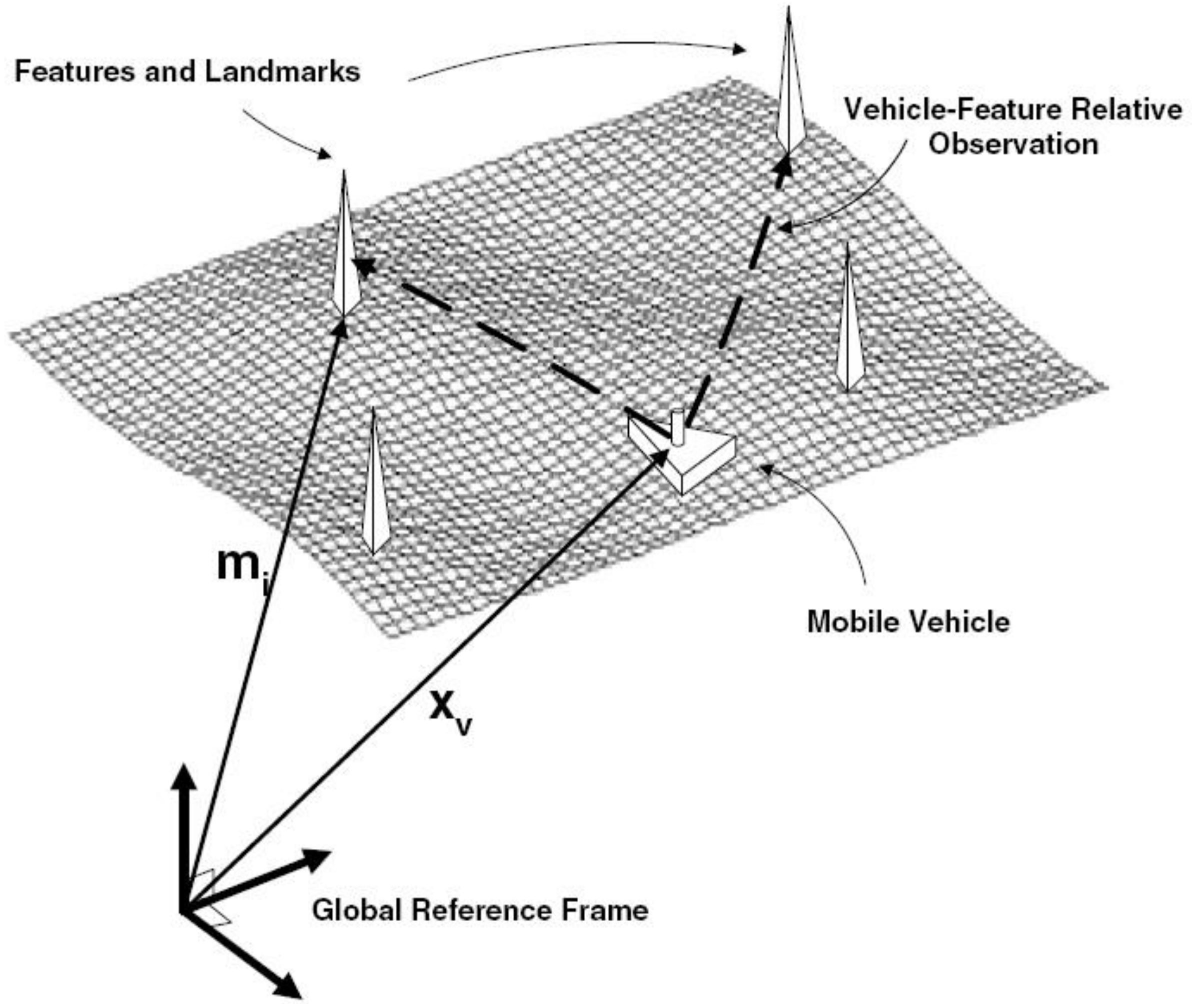
- Online SLAM:

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

Integrations typically done one at a time

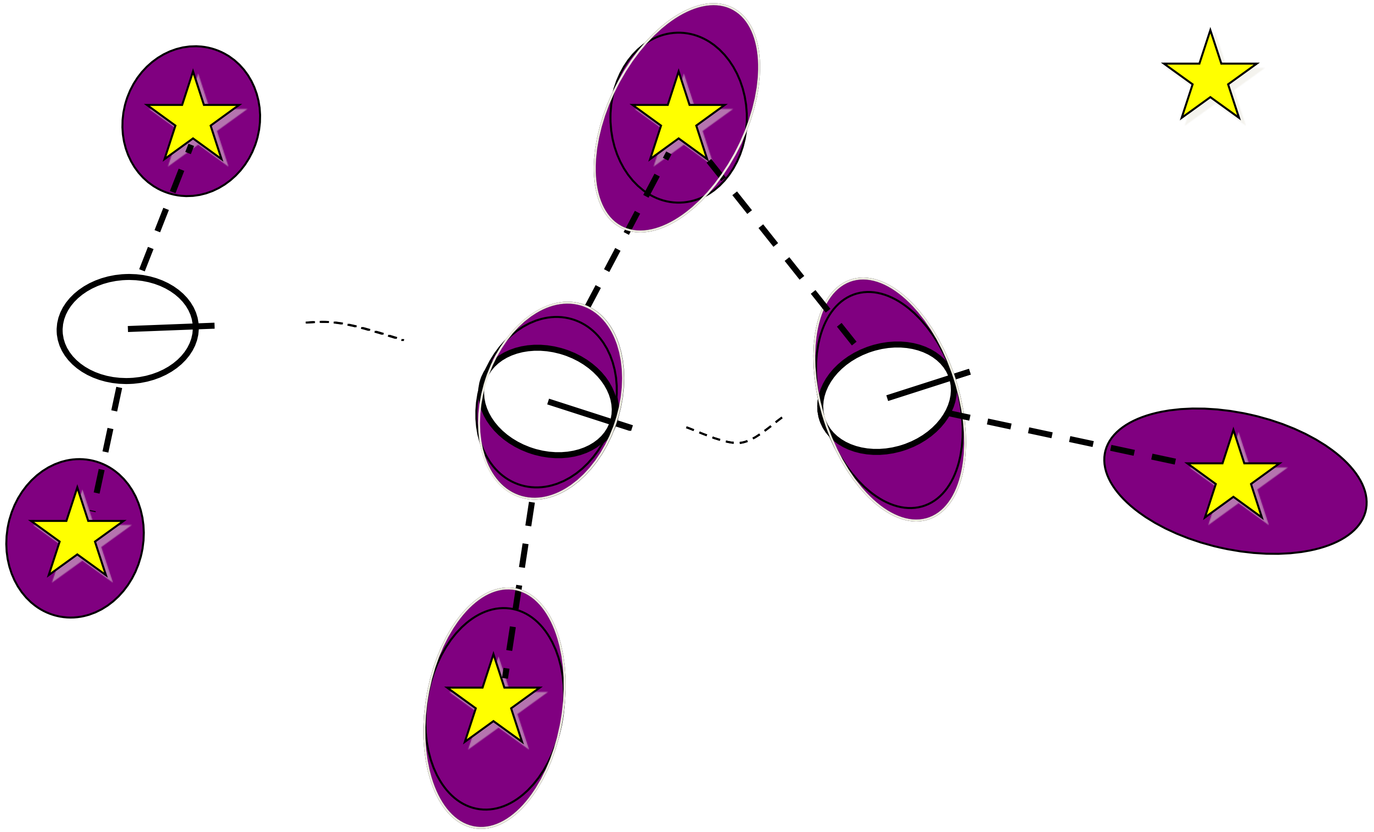
Estimates most recent pose and map!

Structure of the Landmark-based SLAM-Problem



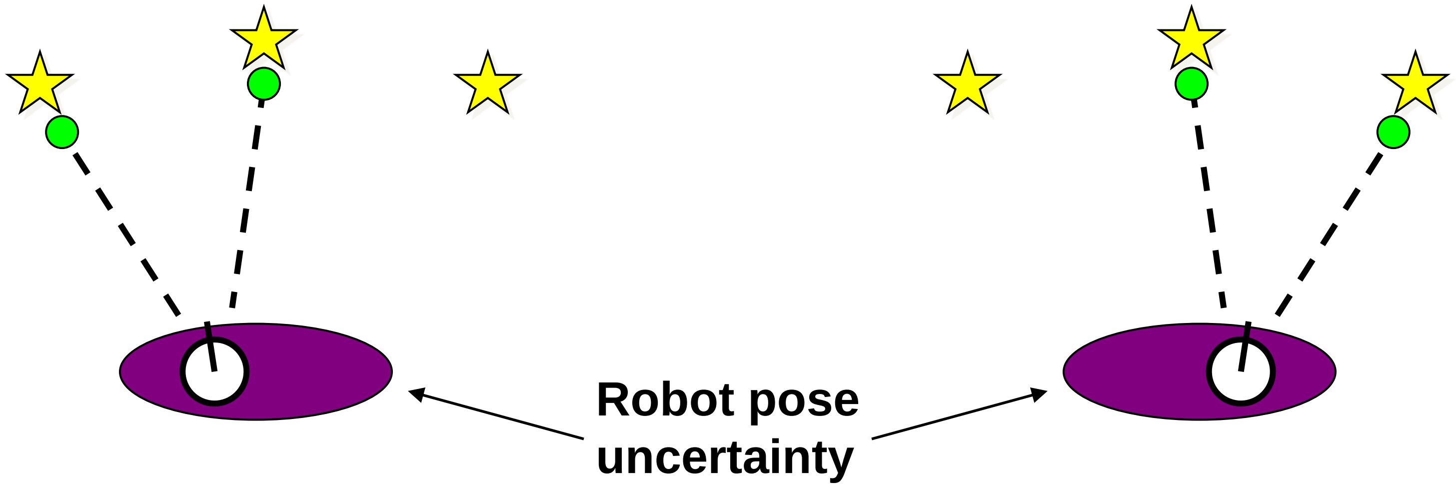
Why is SLAM a Difficult Problem?

SLAM: robot path and map are both **unknown**



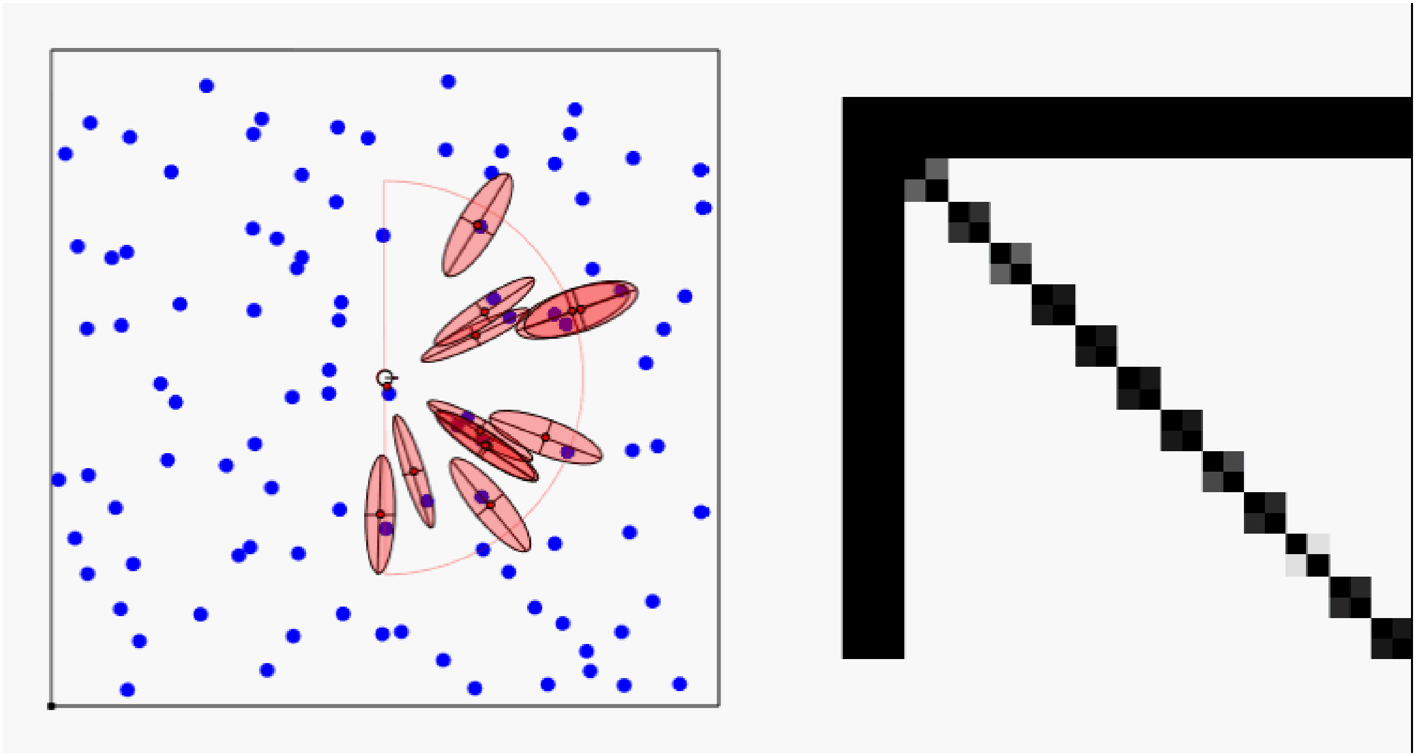
Robot path error correlates errors in the map

Why is SLAM a Difficult Problem?



- In the real world, the mapping between observations and landmarks is unknown
- Picking wrong data associations can have catastrophic consequences
- Pose error correlates data associations

Classical Solution – The EKF



- Approximate the SLAM posterior with a high-dimensional Gaussian [Smith & Cheesman, 1986] …
- Single hypothesis data association

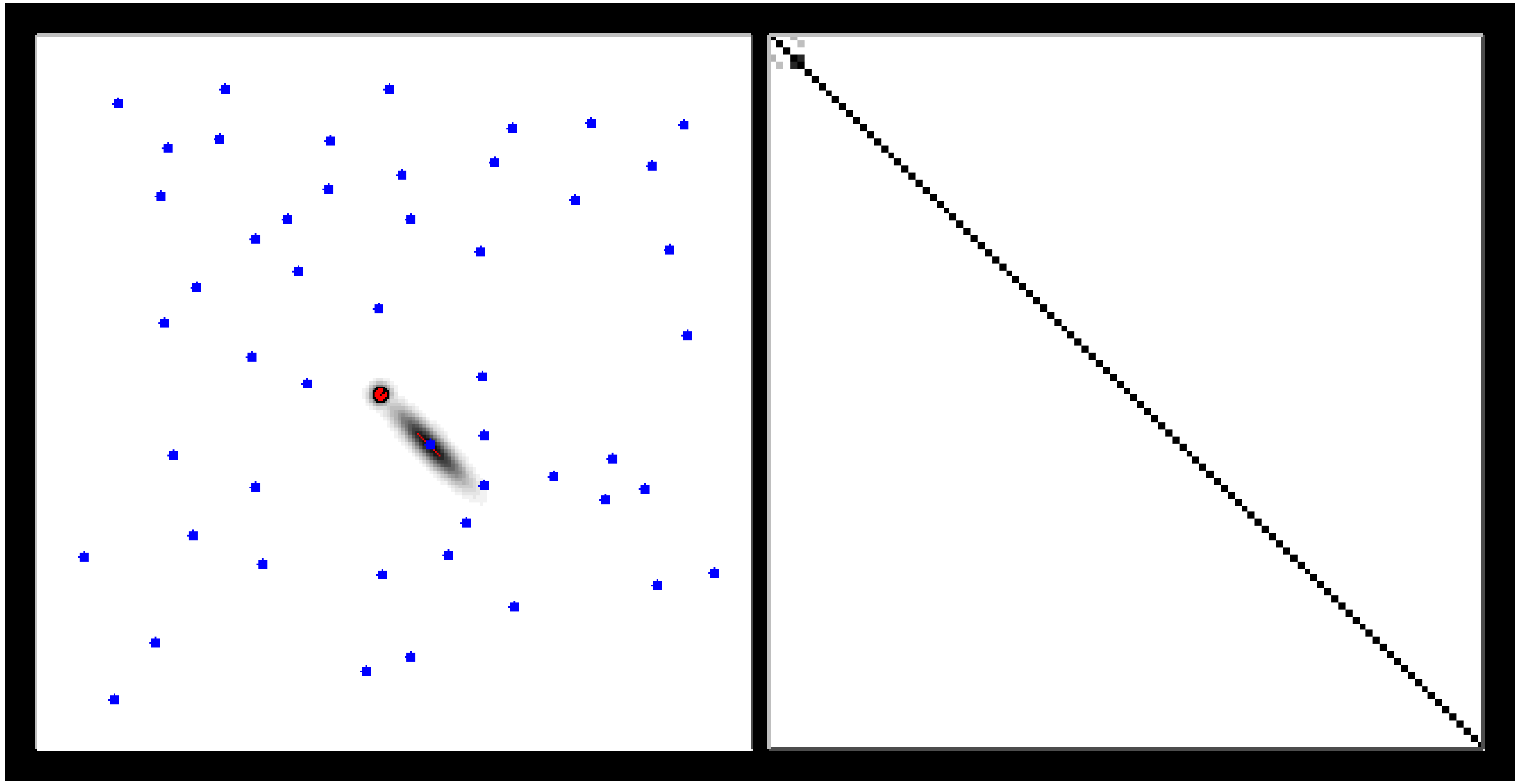
(E)KF-SLAM

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

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

- Can handle hundreds of dimensions

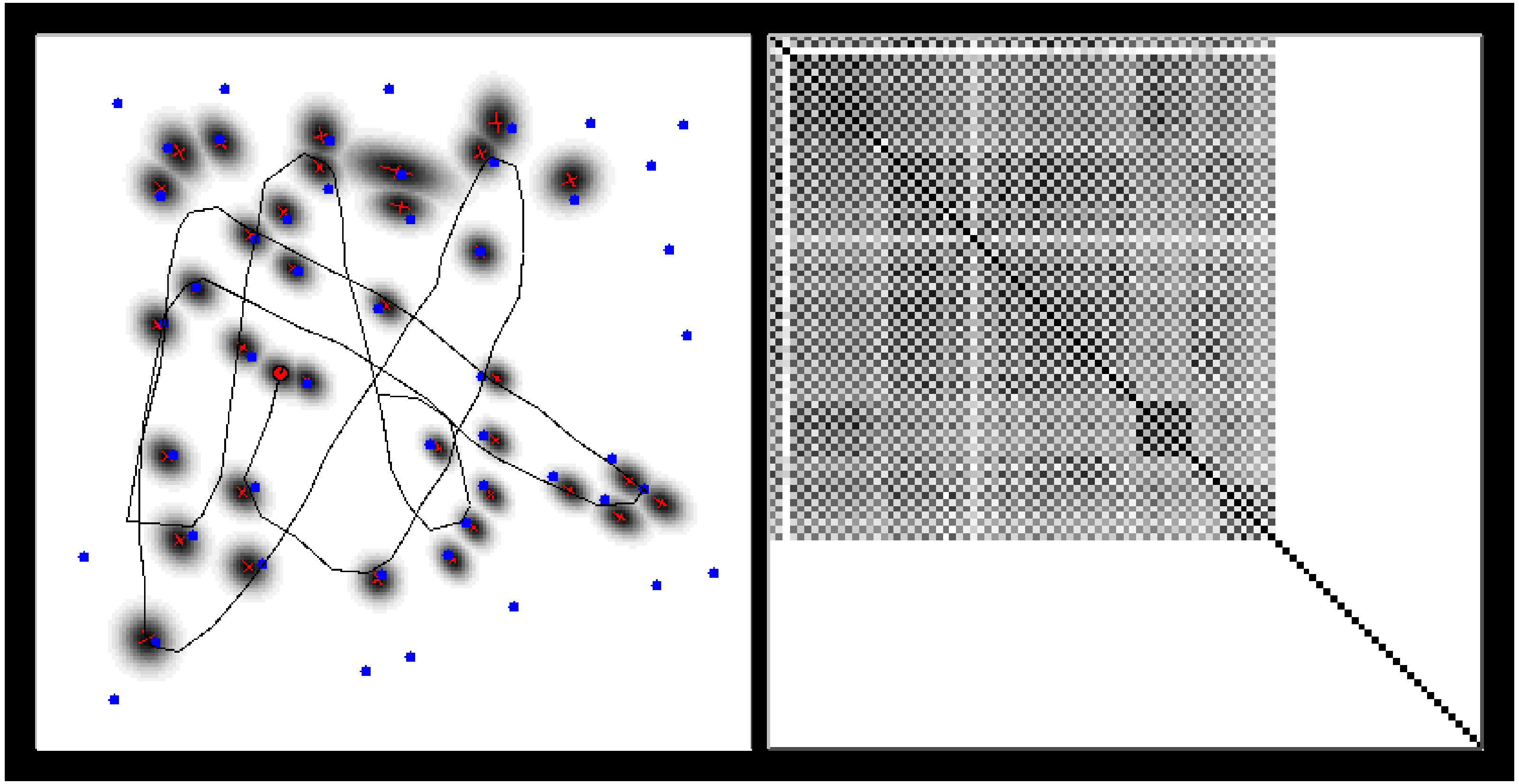
EKF-SLAM



Map

Correlation matrix

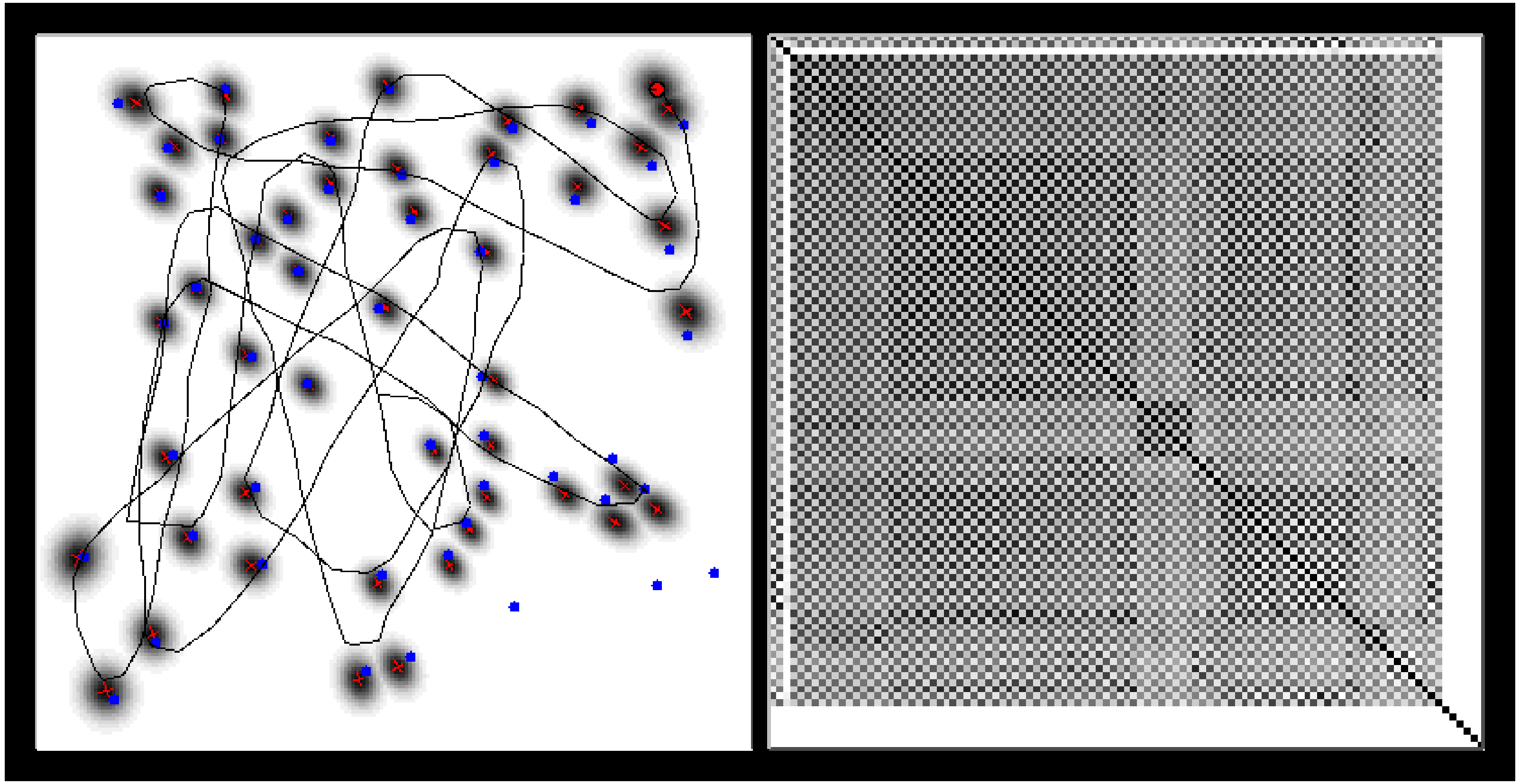
EKF-SLAM



Map

Correlation matrix

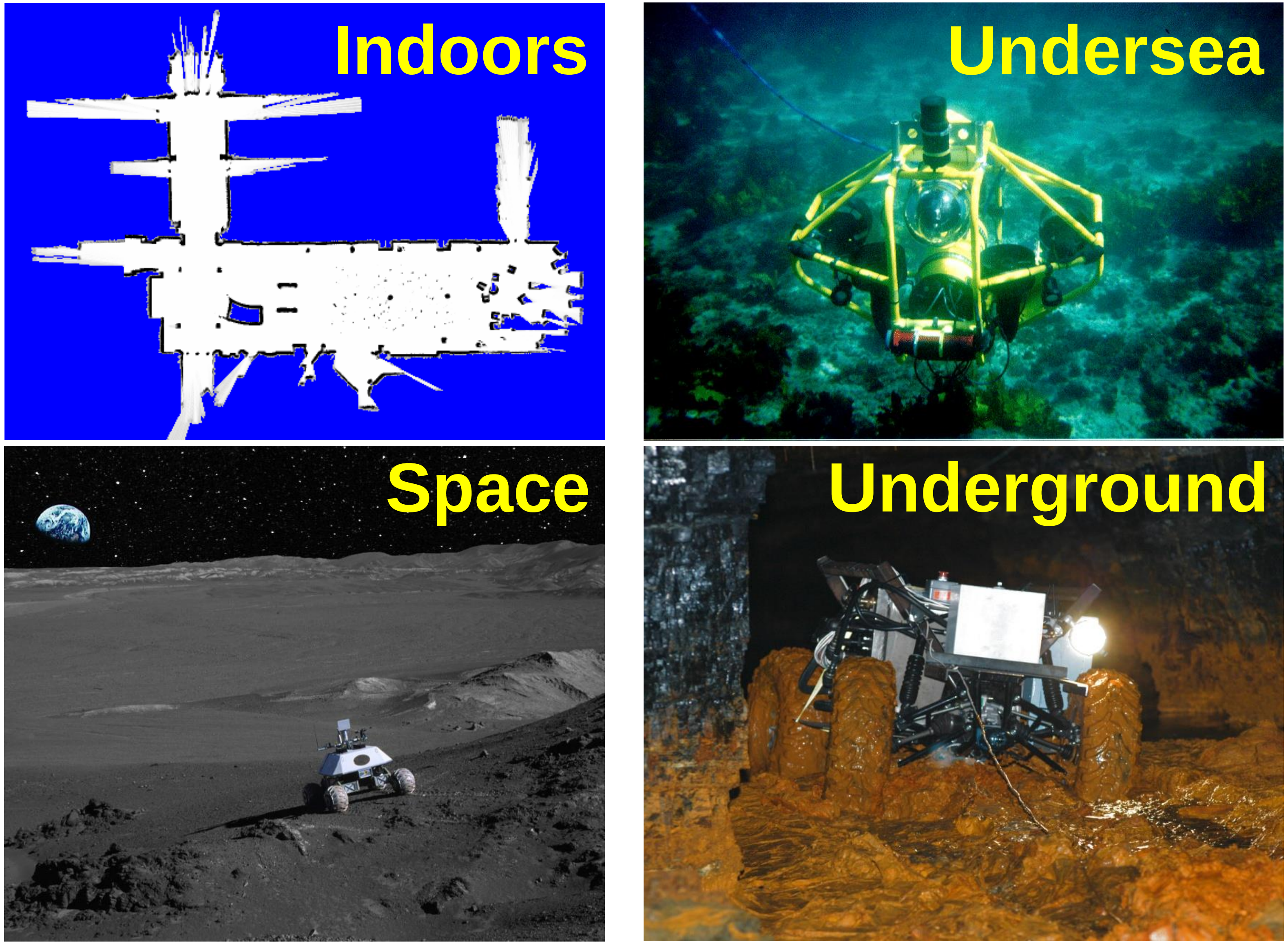
EKF-SLAM



Map

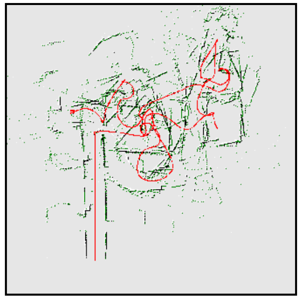
Correlation matrix

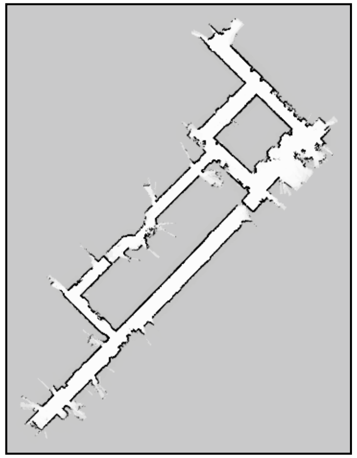
SLAM Applications



Representations

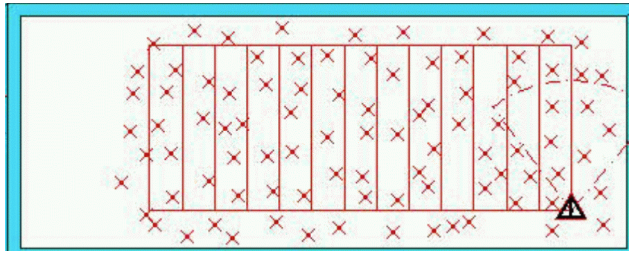
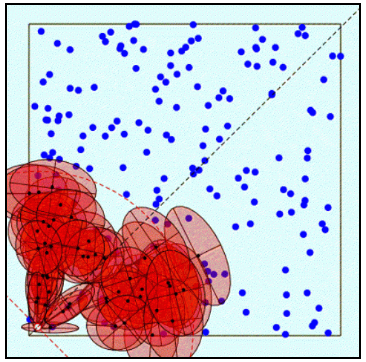
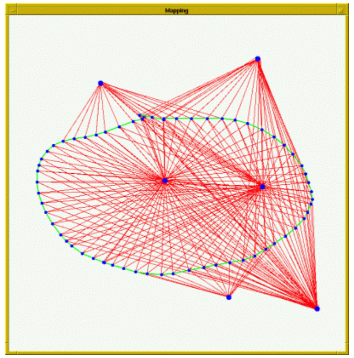
- Grid maps or scans





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

- Landmark-based

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

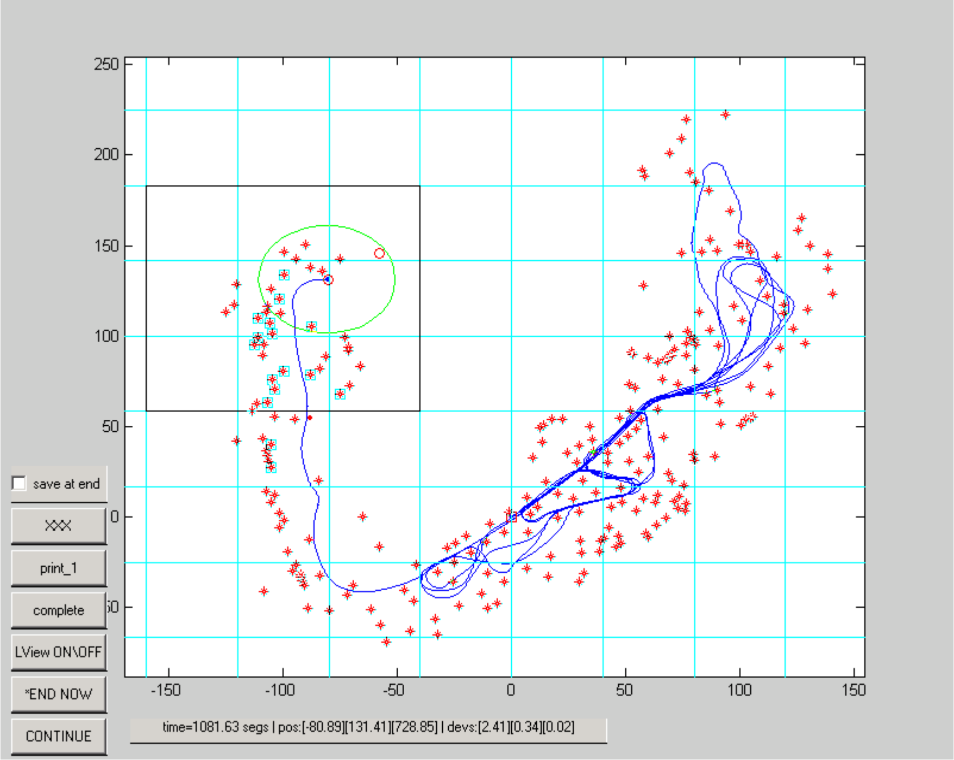
Victoria Park Data Set Vehicle

[courtesy of E. Nebot]

Victoria Park Data Set

[courtesy of E. Nebot]

Map and Trajectory

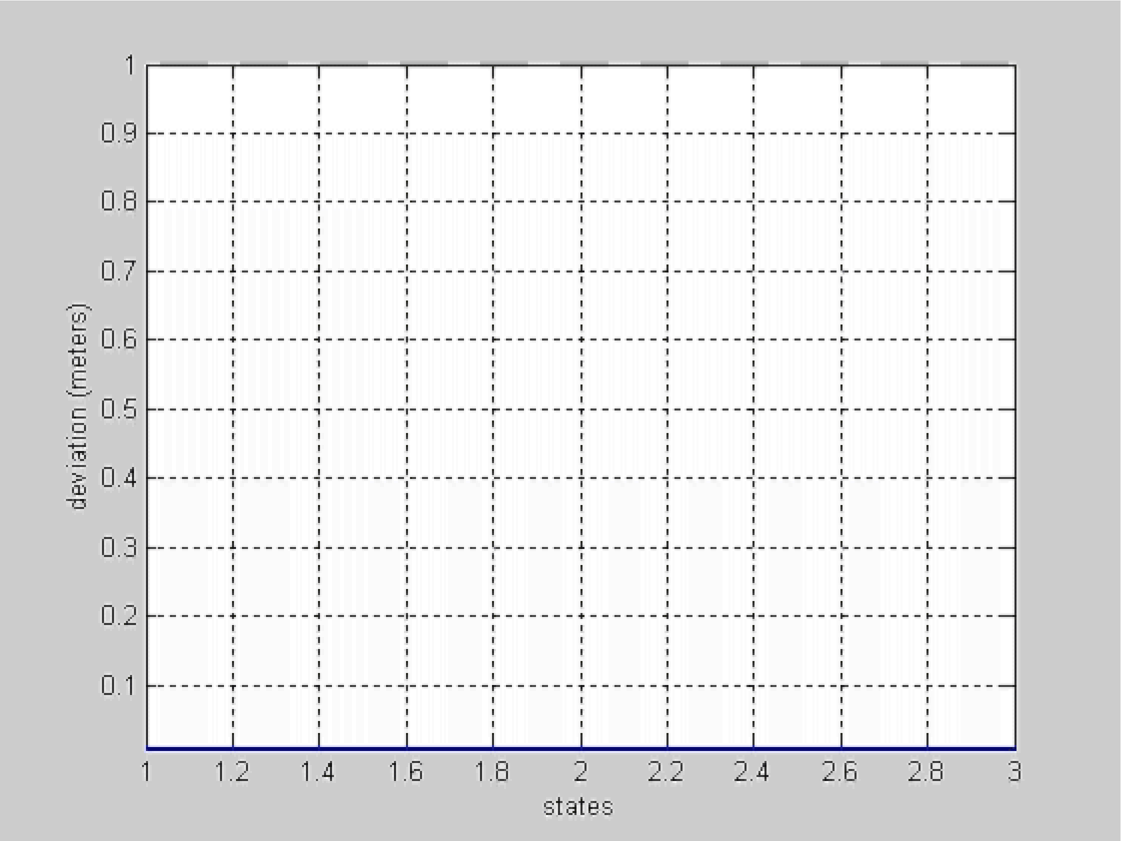


Landmarks

Covariance

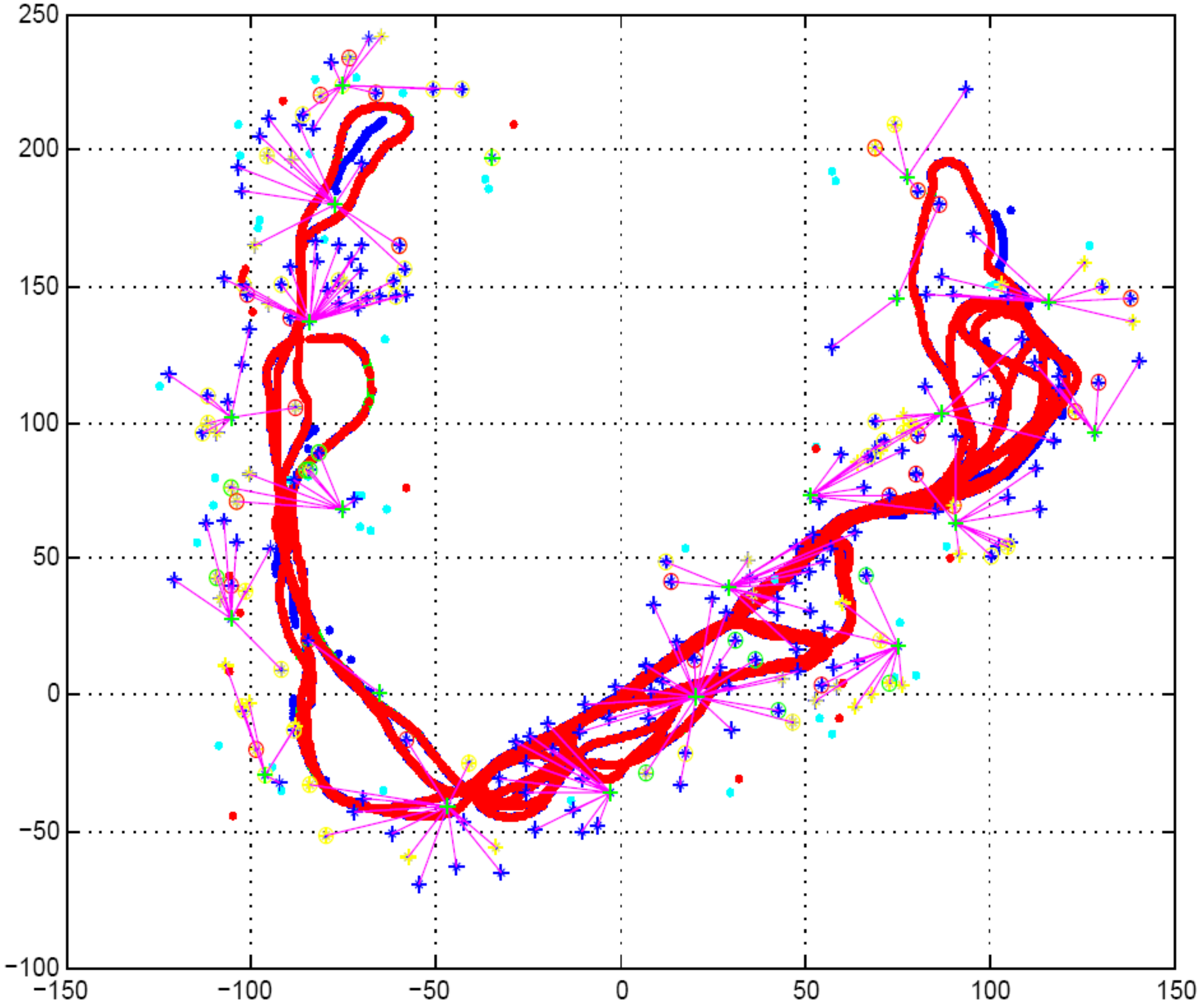
[courtesy of E. Nebot]

Landmark Covariance

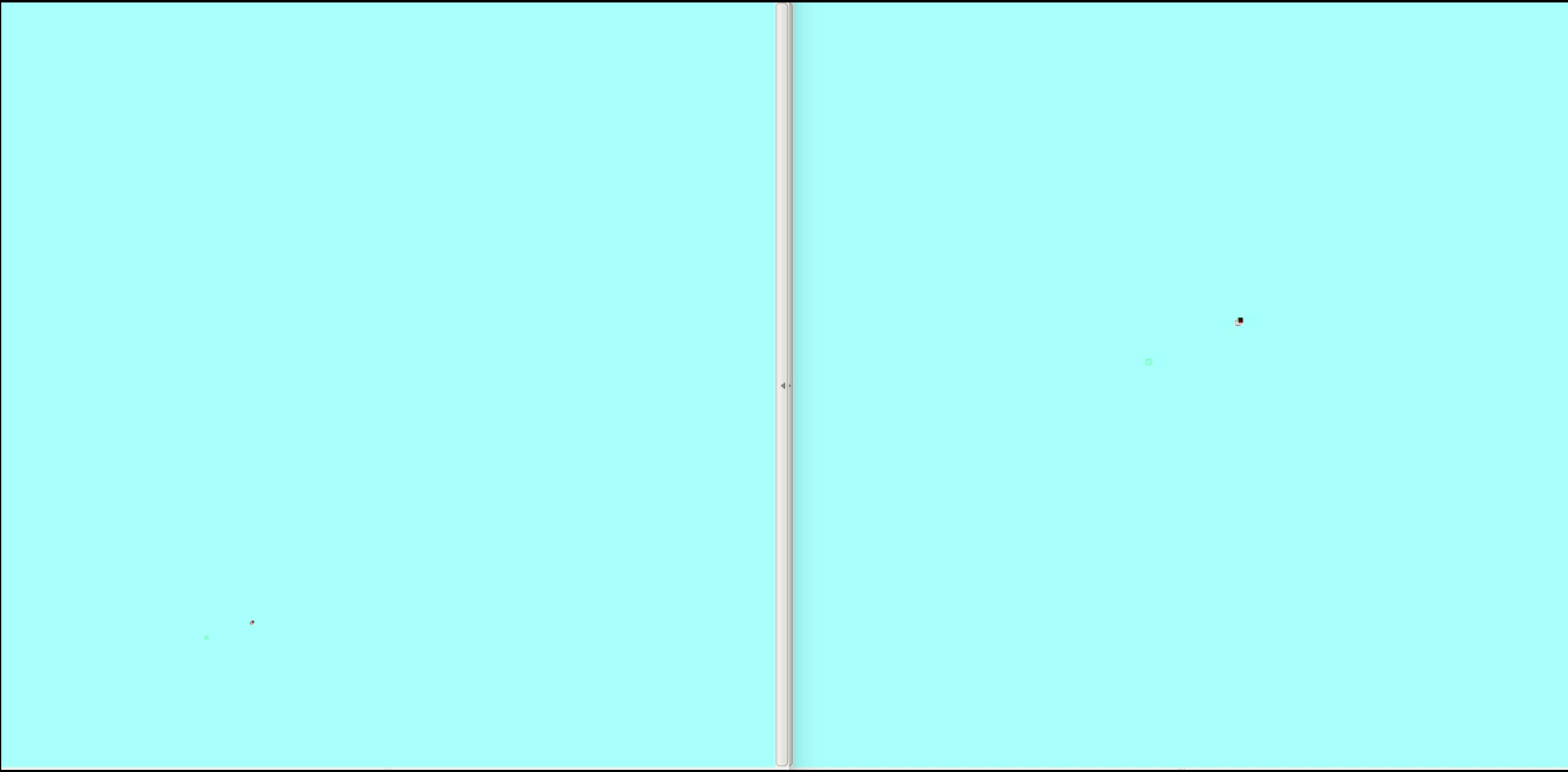


[courtesy of E. Nebot]

Estimated Trajectory



[courtesy of E. Nebot]

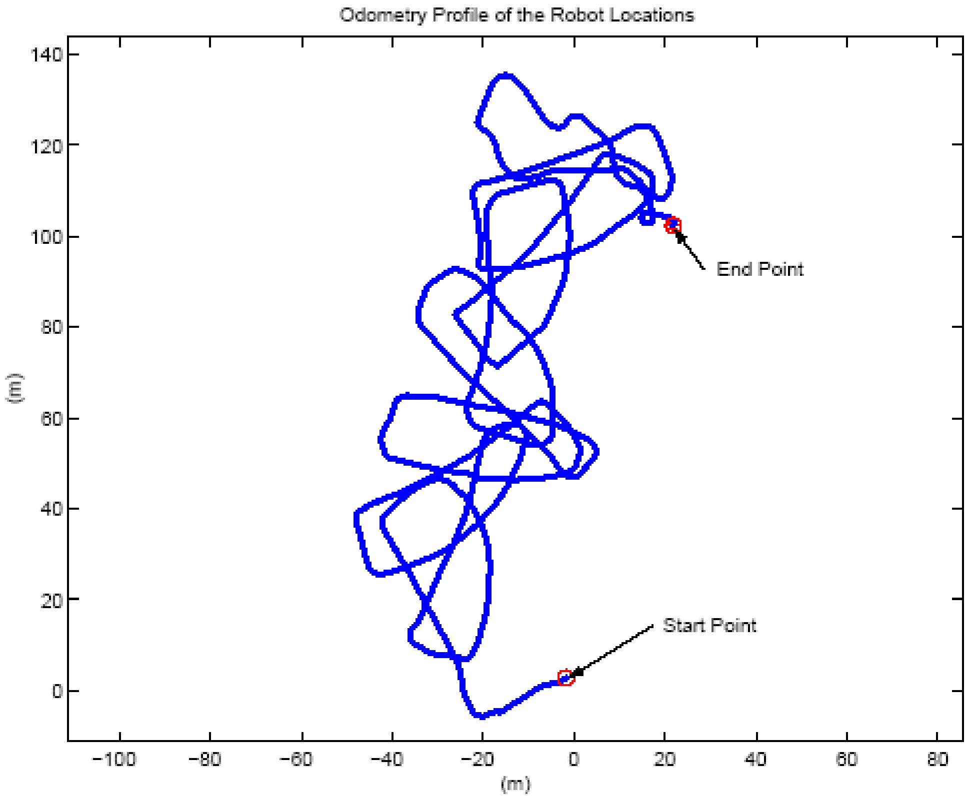


Xiaotong Shen, https://www.youtube.com/watch?v=BIOJSNHYSbc

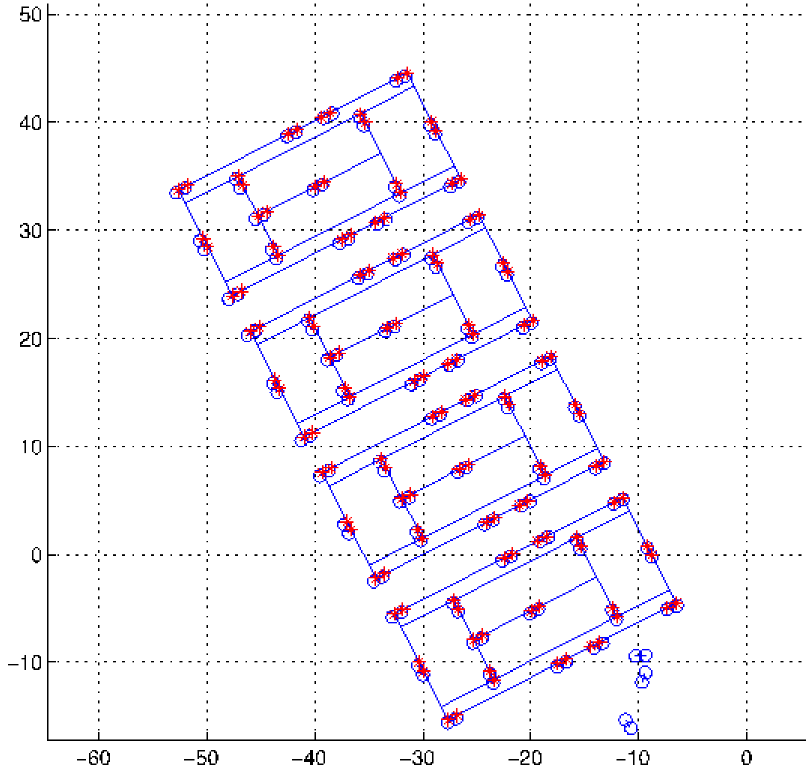
EKF SLAM Application

[courtesy by John Leonard]

EKF SLAM Application



odometry



estimated trajectory

[courtesy by John Leonard]

Approximations for SLAM

- Local submaps
  [Leonard et al.99, Bosse et al. 02, Newman et 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]

EKF-SLAM Summary

- 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.

CHAPTER 4

RECURSIVE STATE ESTIMATION

- NON-PARM. ←
- PARAM. ←

1) LOCALIZE IN A MAP ✓

2) SLAM ✓