Universidade Federal do Paraná

Especialização em Inteligência Artificial Aplicada

Mobile Robotics

Simultaneous Localization and Mapping

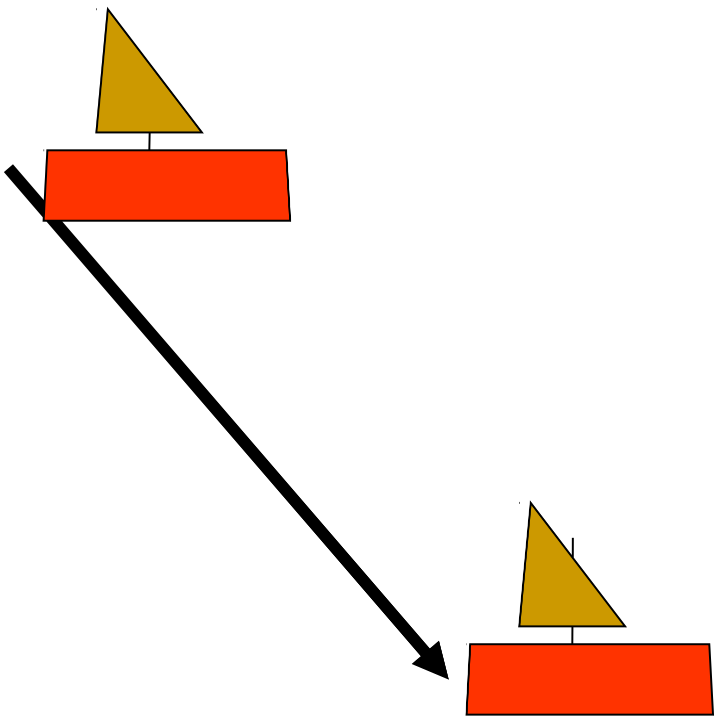
SLAM

Prof. Eduardo Todt

2019

Estimando a posição – dead reckoning

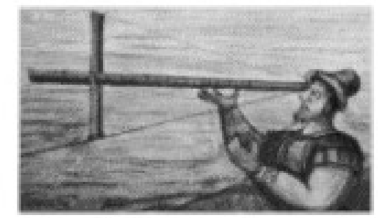
- Bowditch, 1837
  - sem observação estelar



- Last known fix: 51°30.0'S, 80°59.5'W
- Time of last fix: 1999-03-24, 00:10:23 UT
- True Course: 119.3°
- Compass variation: 18°E
- Compass deviation: 2.5°W
- Speed 10.3 kts
- Current drift: 115°, 1.0 kts
- Time of new fix: 23:40:01.
  - http://jsc.nasa.gov

Estimando posição – referências externas

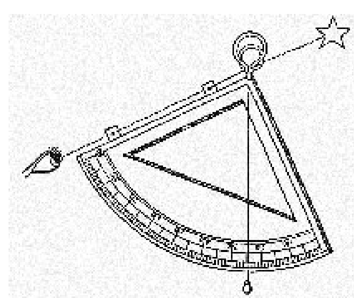
- **Ex: navegação celestial**



ângulo entre horizonte e estrela polar → latitude

longitude?

- em 1714 parlamento Inglaterra ofereceu prêmio 20.000 libras
- variação na hora meio-dia de referência
- 15 graus/hora



http://jsc.nasa.gov

Probabilistic Robotics: SLAM

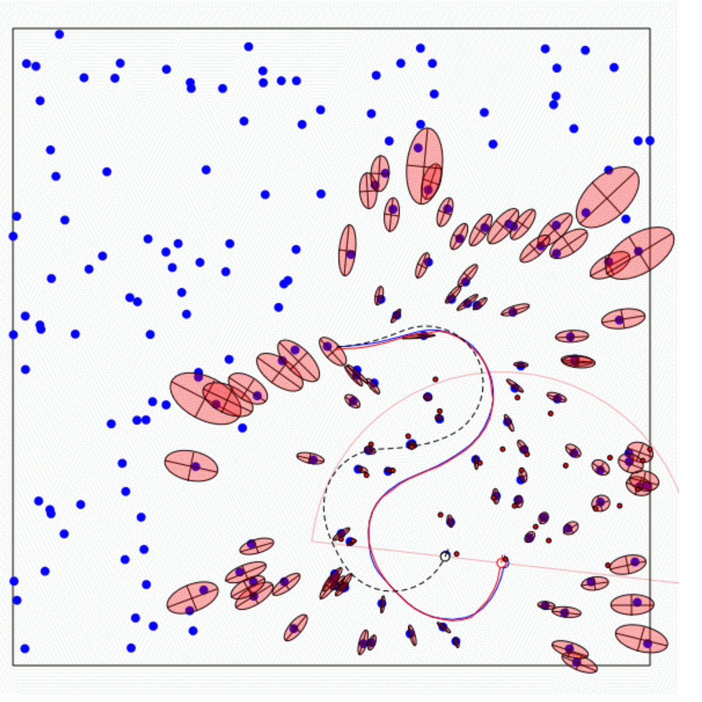
= Simultaneous Localization and Mapping

Sebastian Thrun & Alex Teichman

Stanford Artificial Intelligence Lab

Slide credits: Wolfram Burgard, Dieter Fox, Cyrill Stachniss, Giorgio Grisetti, Maren Bennewitz, Christian Plagemann, Dirk Haehnel, Mike Montemerlo, Nick Roy, Kai Arras, Patrick Pfaff and others

The SLAM Problem



A robot is exploring an unknown, static environment.

Given:

- The robot’s controls
- Observations of nearby features

Estimate:

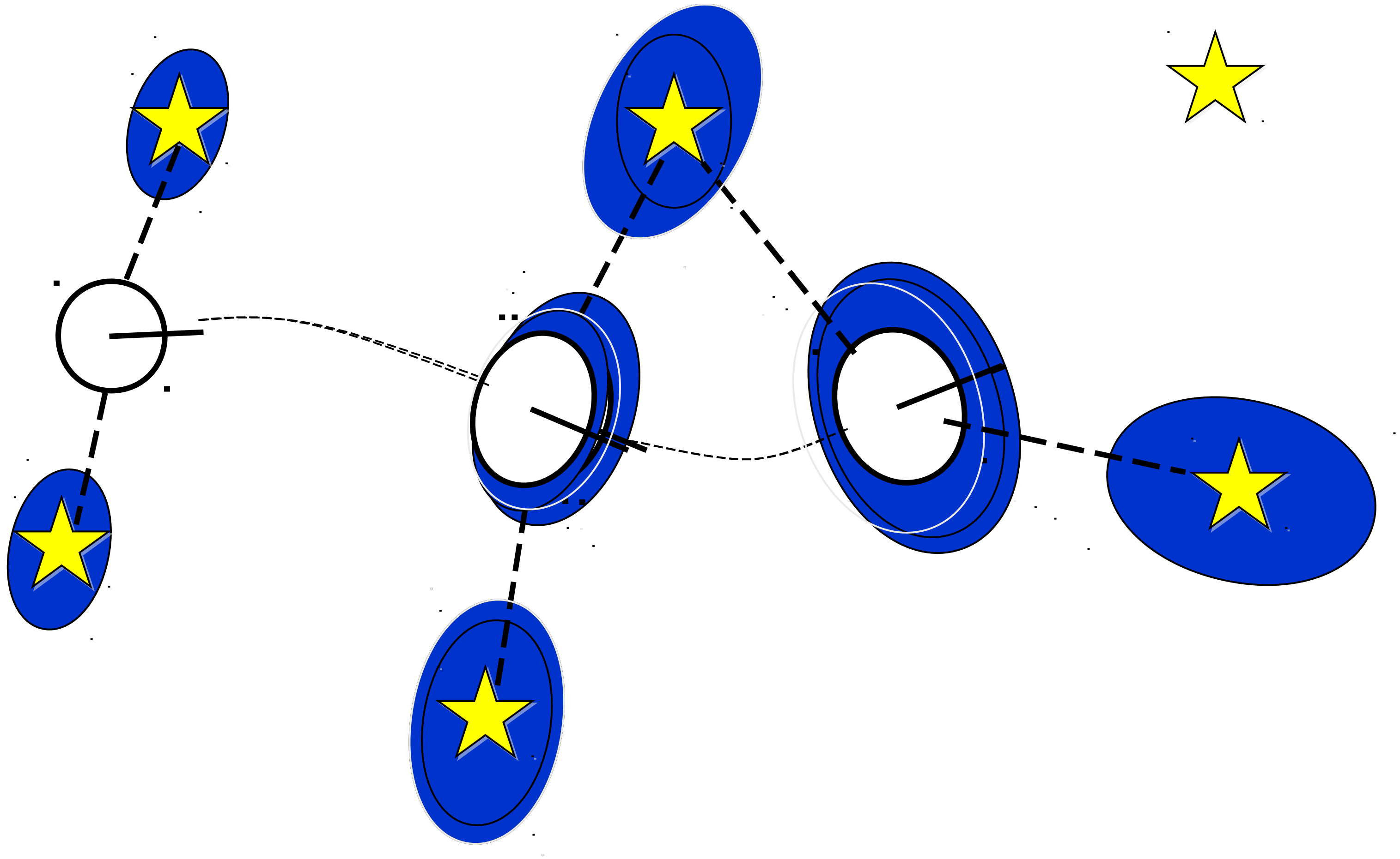
- Map of features
- Path of the robot

Chicken-or-Egg

- SLAM is a chicken-or-egg problem
  - A map is needed for localizing a robot
  - A good pose estimate is needed to build a map
- Thus, SLAM is regarded as a hard problem in robotics
- A variety of different approaches to address the SLAM problem have been presented
- Probabilistic methods outperform most other techniques

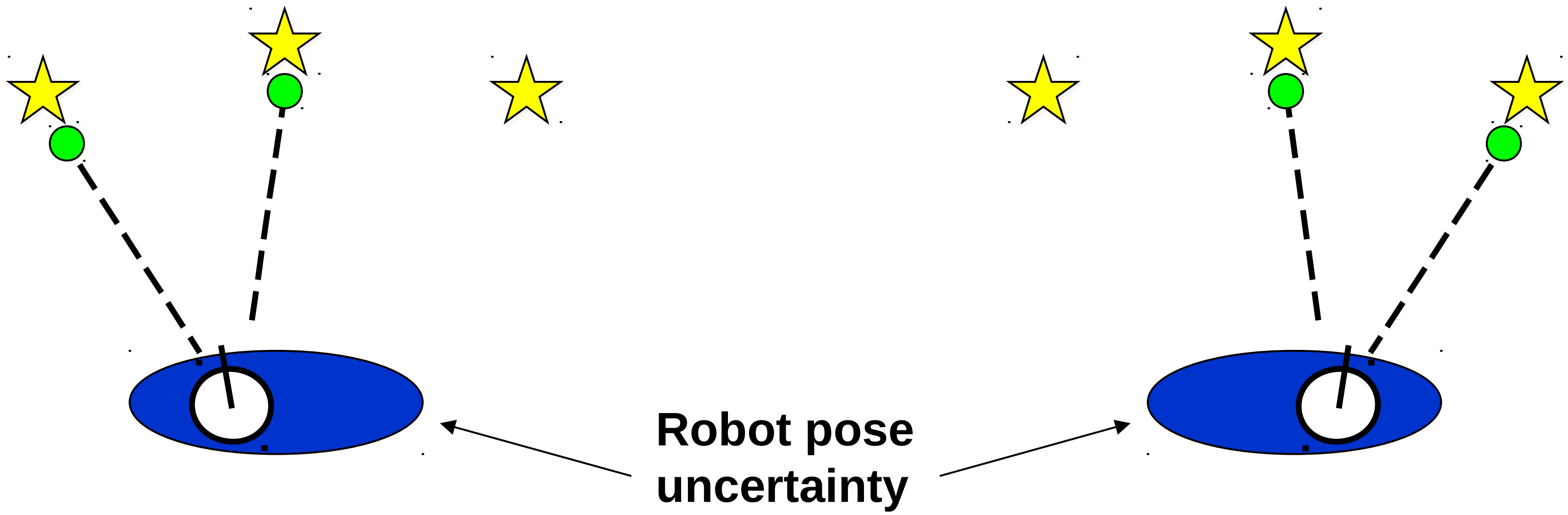
Why is SLAM a hard problem?

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



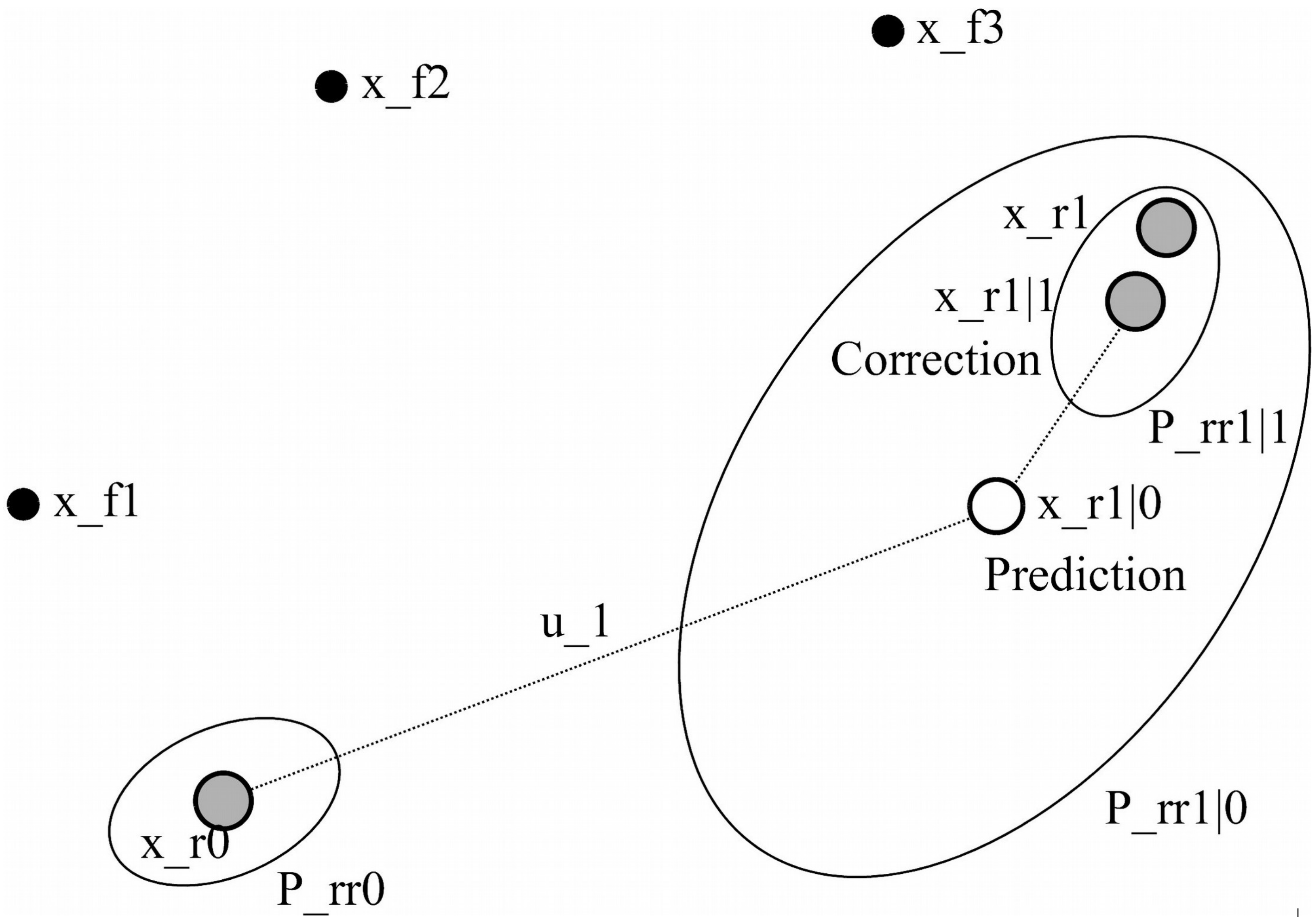
Robot path error correlates errors in the map

Why is SLAM a hard 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

Filtro preditivo de Kalman



Andrade-Cetto, 2002

SLAM:
Simultaneous Localization and Mapping

- Full SLAM:

Estimates entire path and map!

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

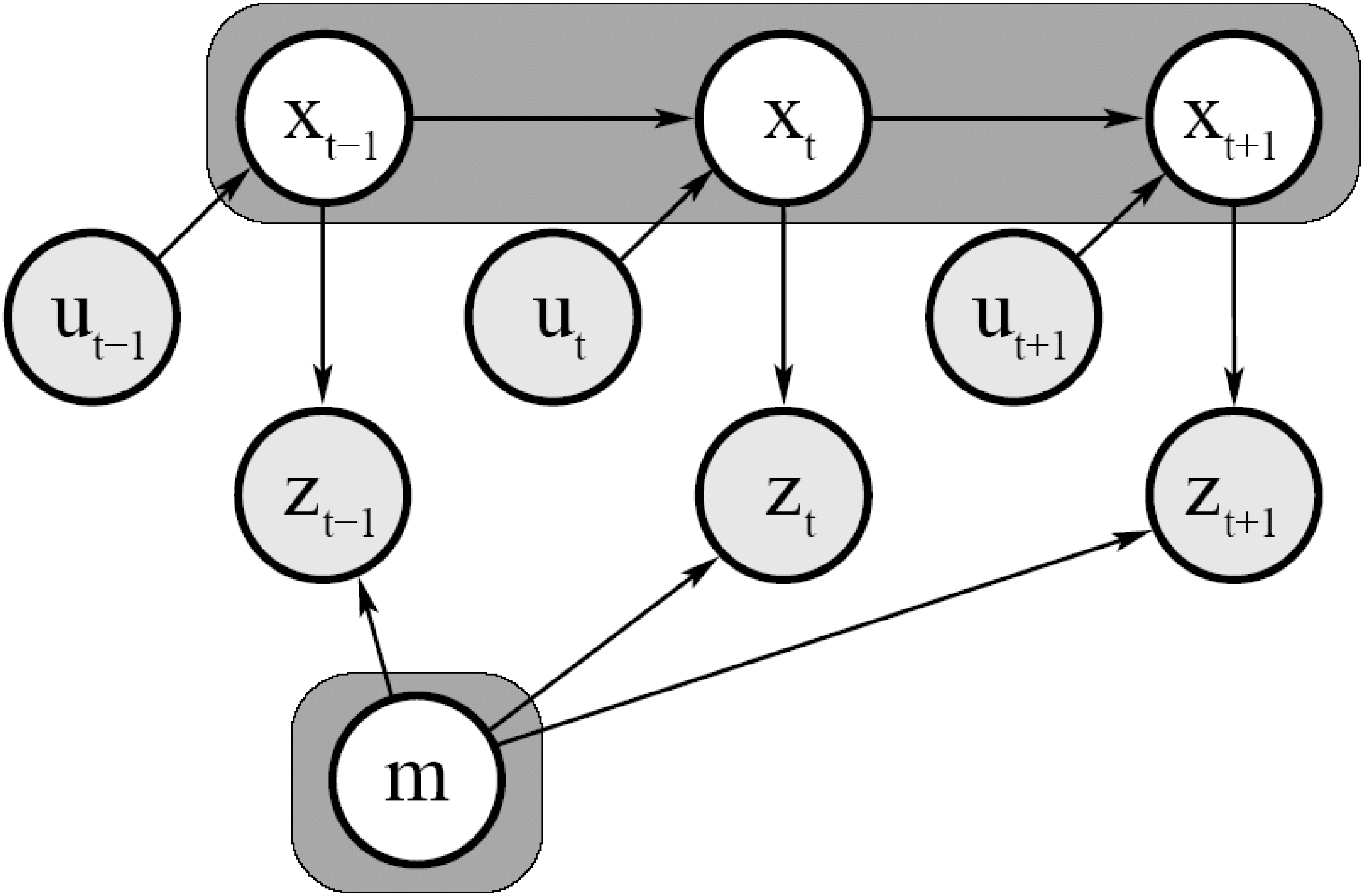
- Online SLAM:

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

Integrations typically done one at a time

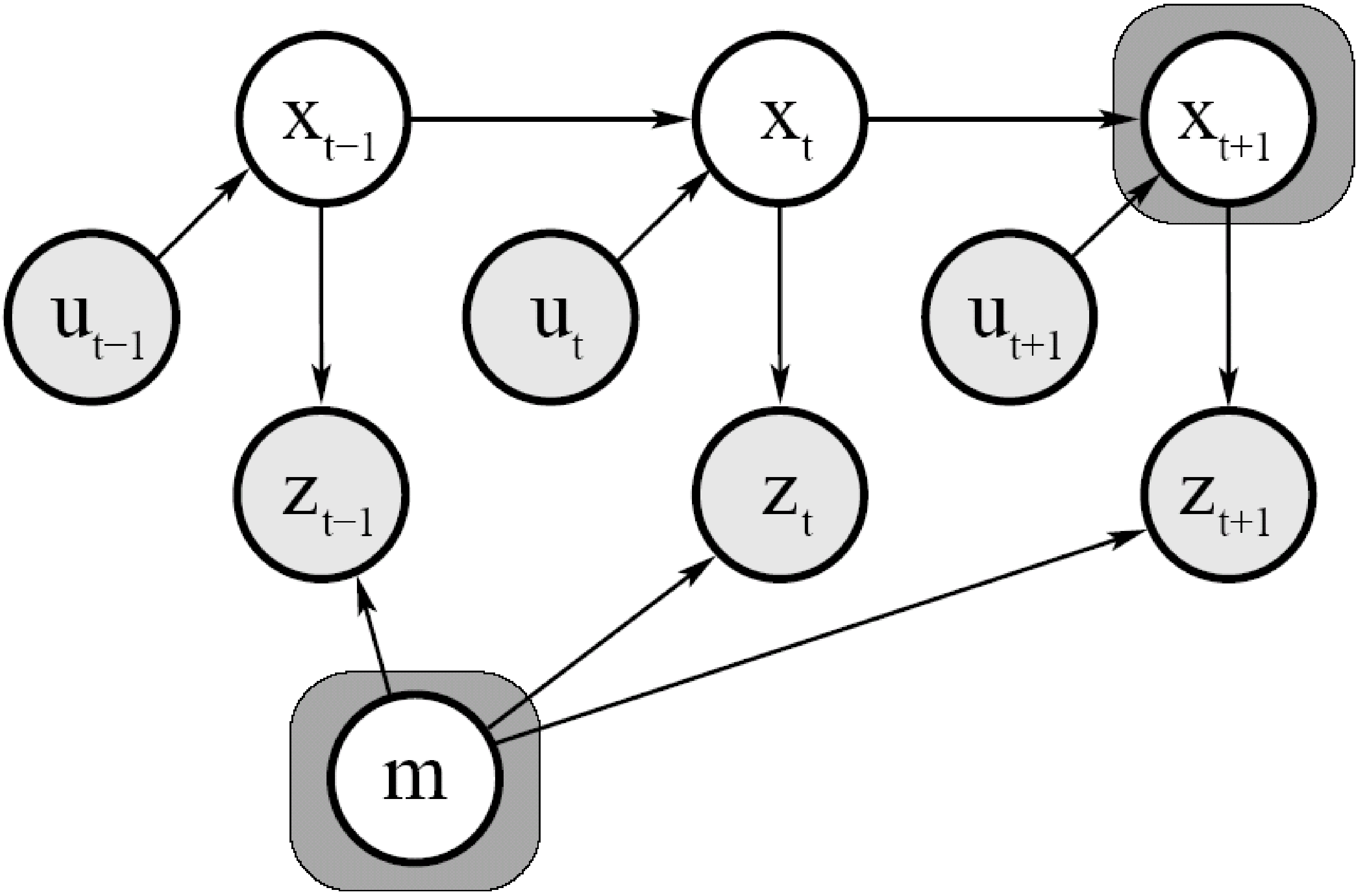
Estimates most recent pose and map!

Graphical Model of Full SLAM:



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

Graphical Model of Online SLAM:



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

Techniques for Generating Consistent Maps

- Scan matching
- EKF SLAM
- FastSLAM
- Probabilistic mapping with a single map and a posterior about poses
  Mapping + Localization
- GraphSLAM, SEIF

Kalman Filter Algorithm

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

1. Prediction:
2. $\bar{\mu}_t = A_t \mu_{t-1} + B_t u_t$
3. $\bar{\Sigma}_t = A_t \Sigma_{t-1} A_t^T + R_t$
4. Correction:
5. $K_t = \bar{\Sigma}_t C_t^T (C_t \bar{\Sigma}_t C_t^T + Q_t)^{-1}$
6. $\mu_t = \bar{\mu}_t + K_t (z_t - C_t \bar{\mu}_t)$
7. $\Sigma_t = (I - K_t C_t) \bar{\Sigma}_t$
8. Return μ_t, Σ_t

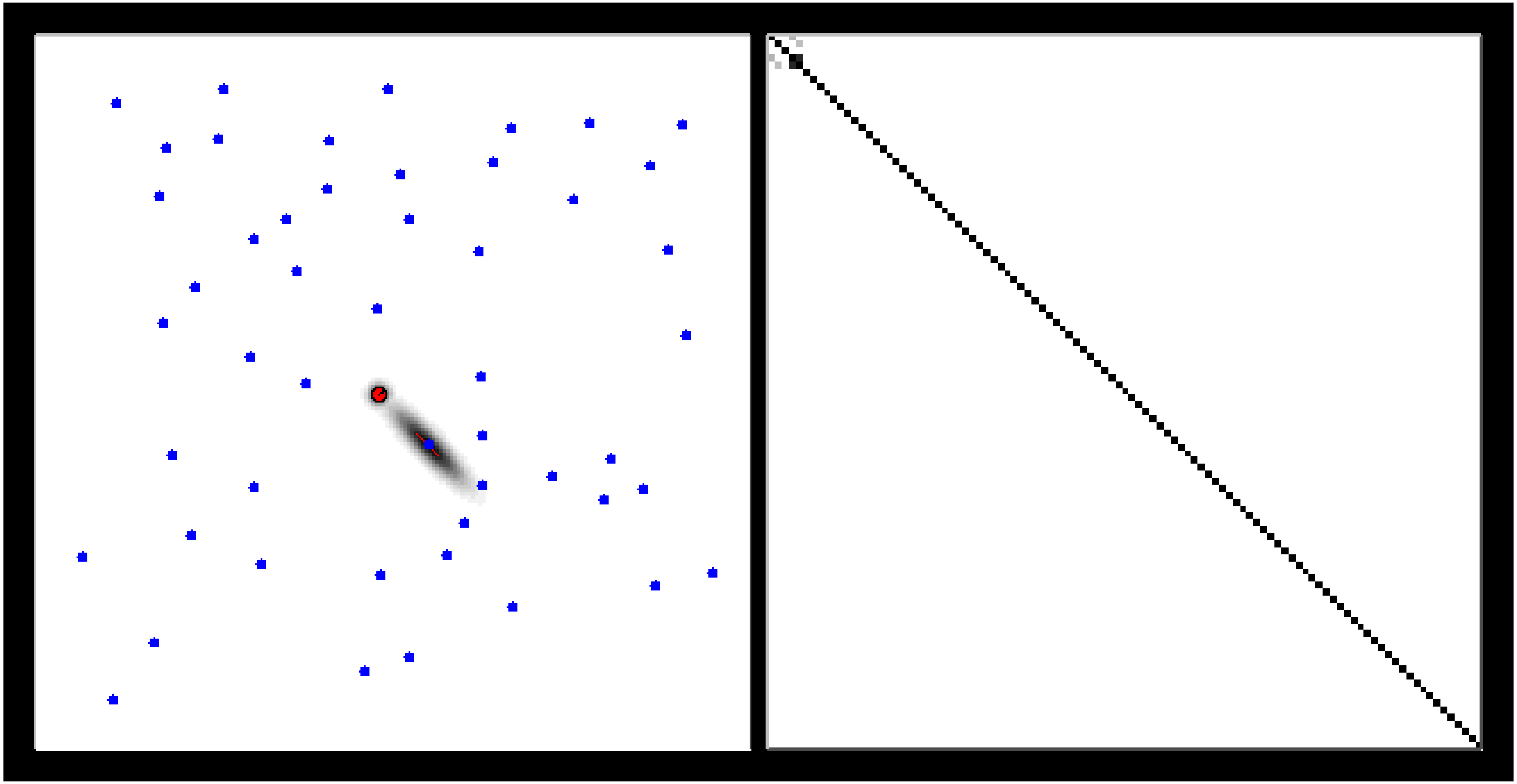
(E)KF-SLAM

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

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

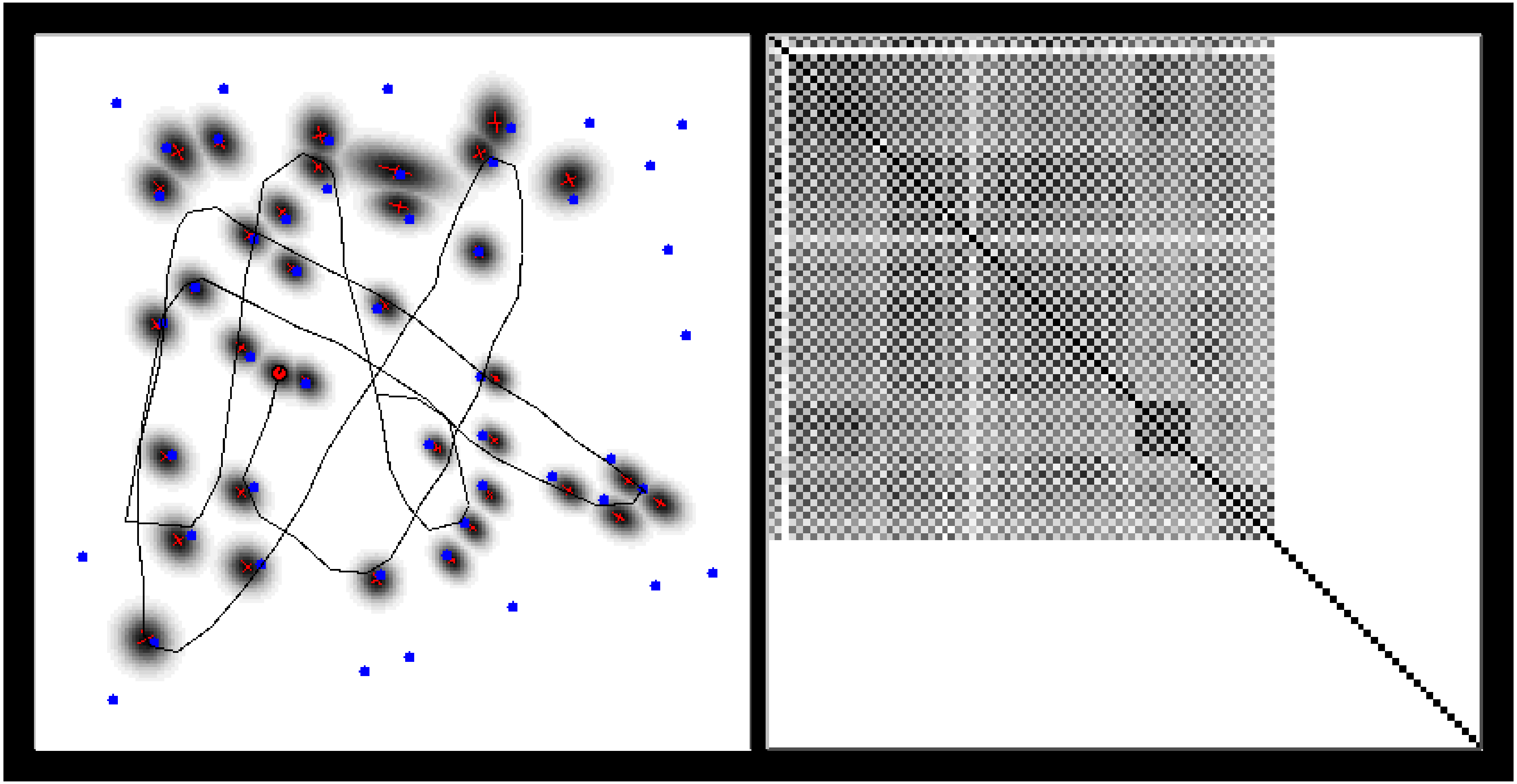
- Can handle hundreds of dimensions

EKF-SLAM



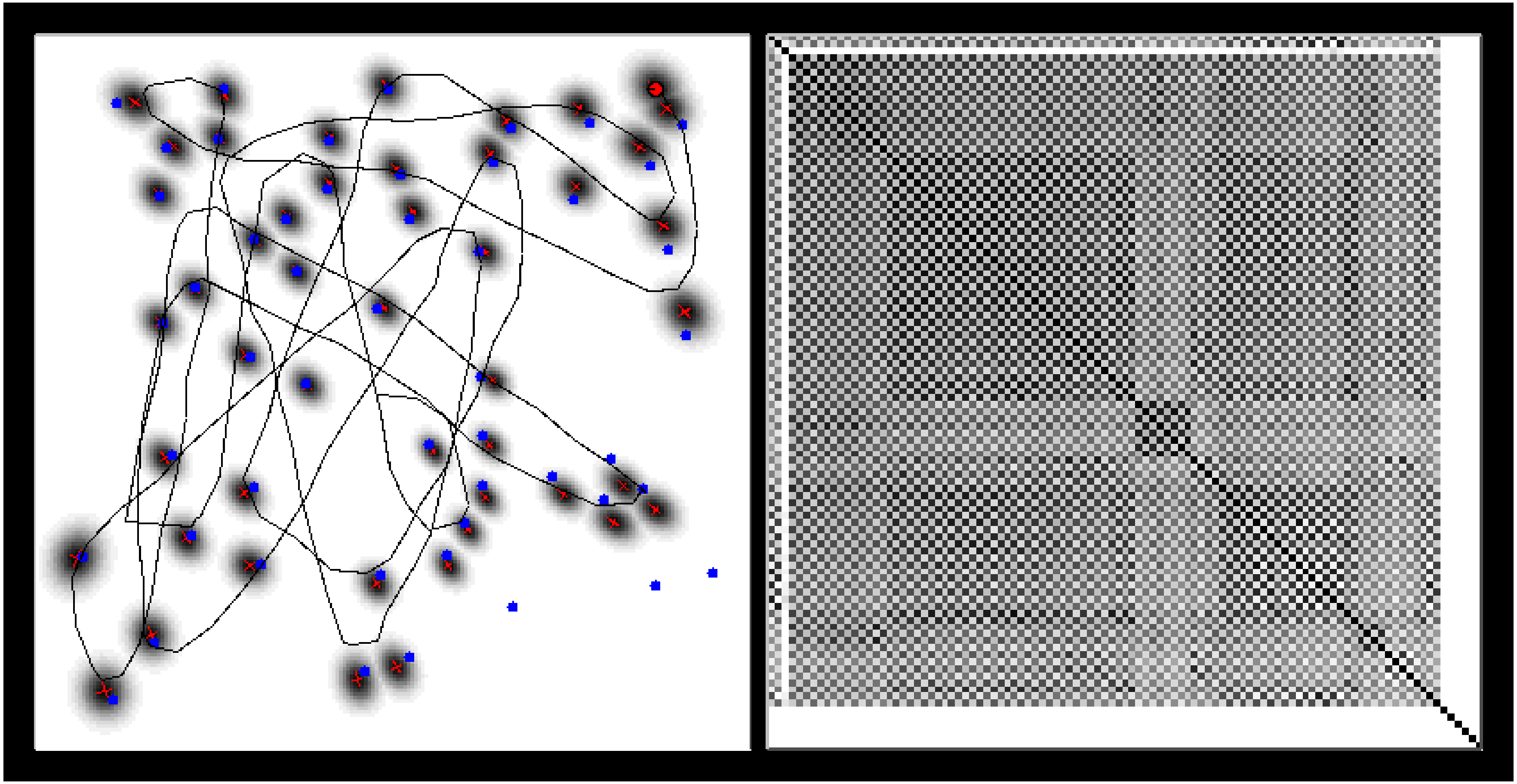
Map Correlation matrix

EKF-SLAM



Map Correlation matrix

EKF-SLAM



Map Correlation matrix

Properties of KF-SLAM (Linear Case)

[Dissanayake et al., 2001]

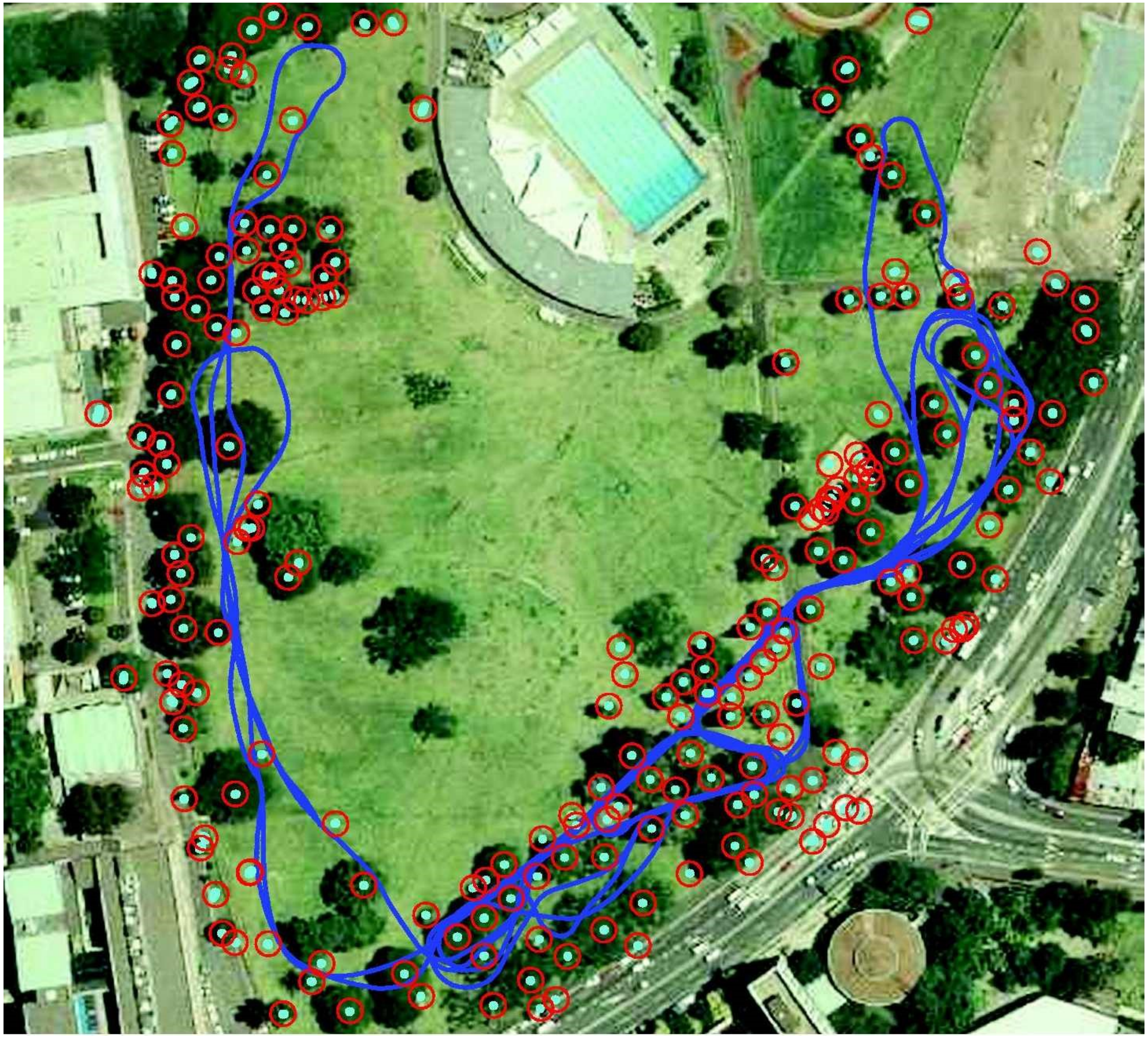
Theorem:

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

Theorem:

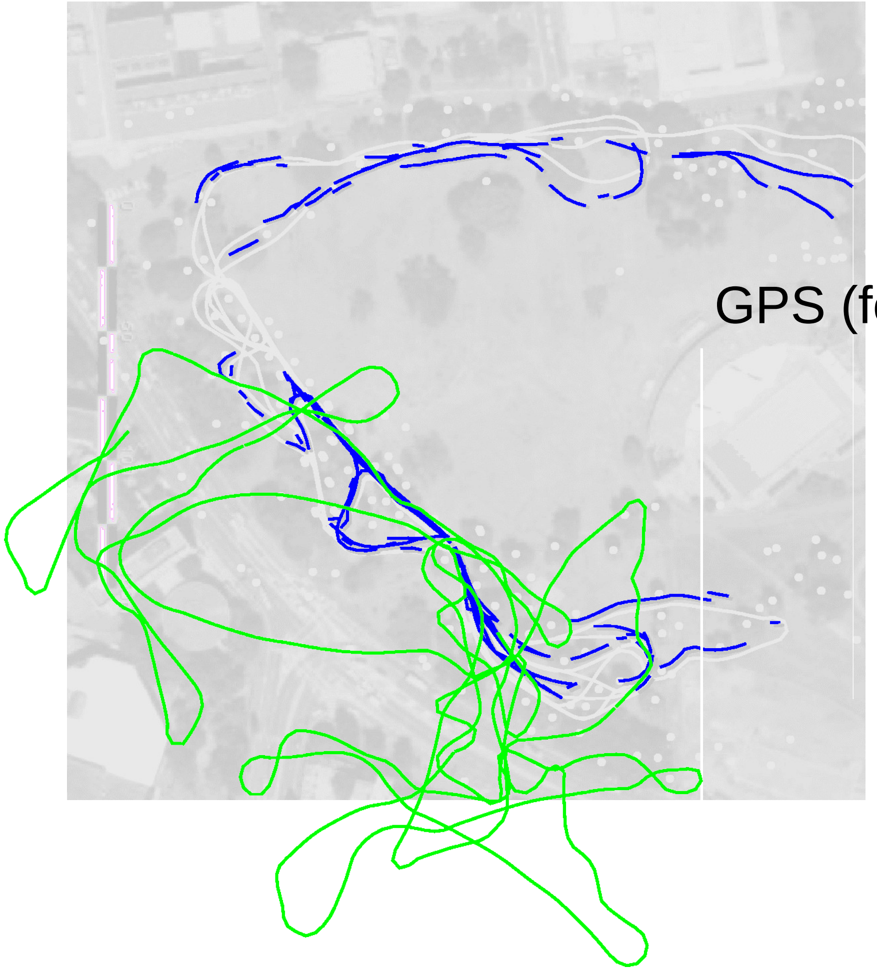
In the limit the landmark estimates become fully correlated

Victoria Park Data Set

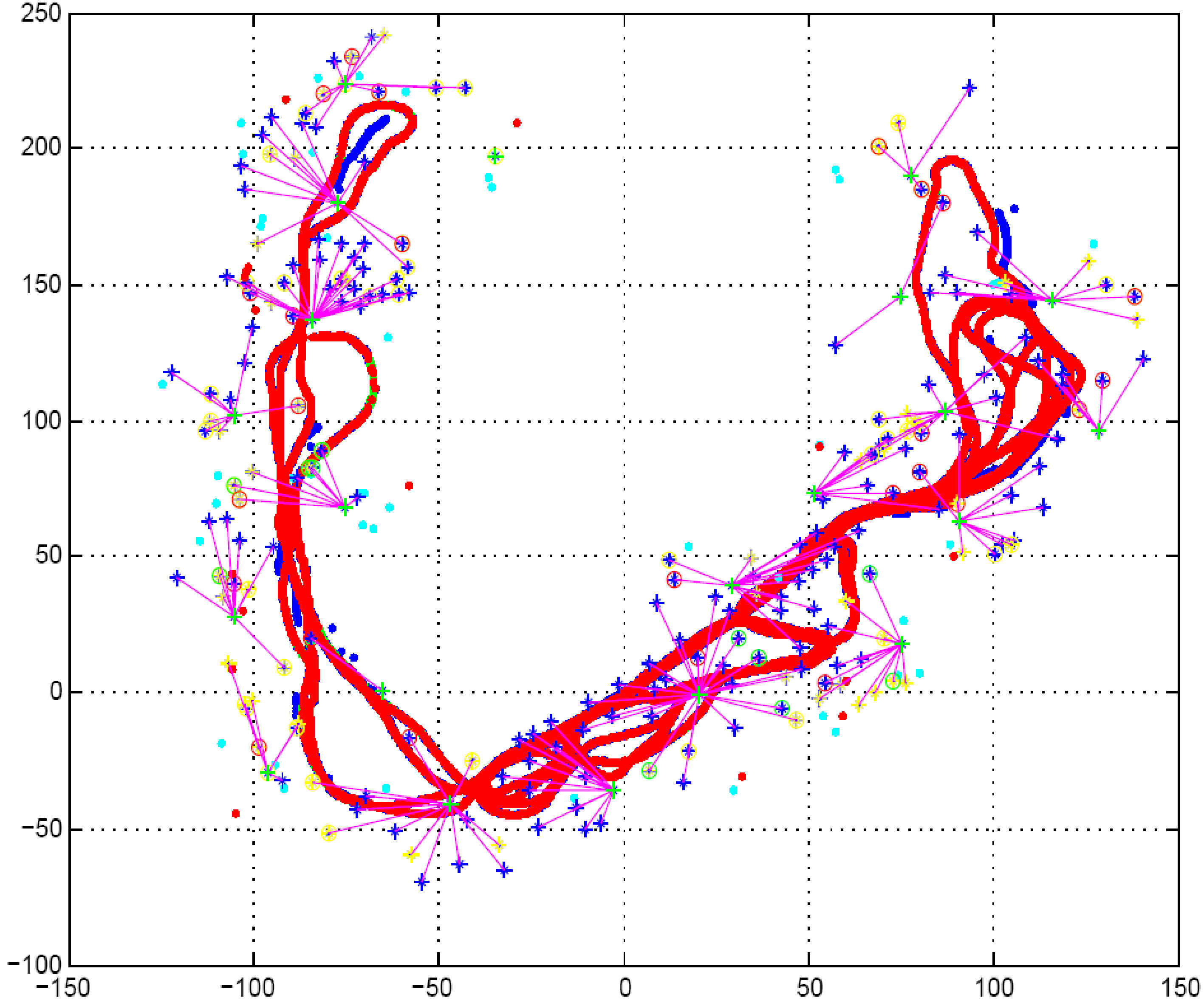


[courtesy by E. Nebot]

Raw Odometry (no SLAM)



Estimated Trajectory

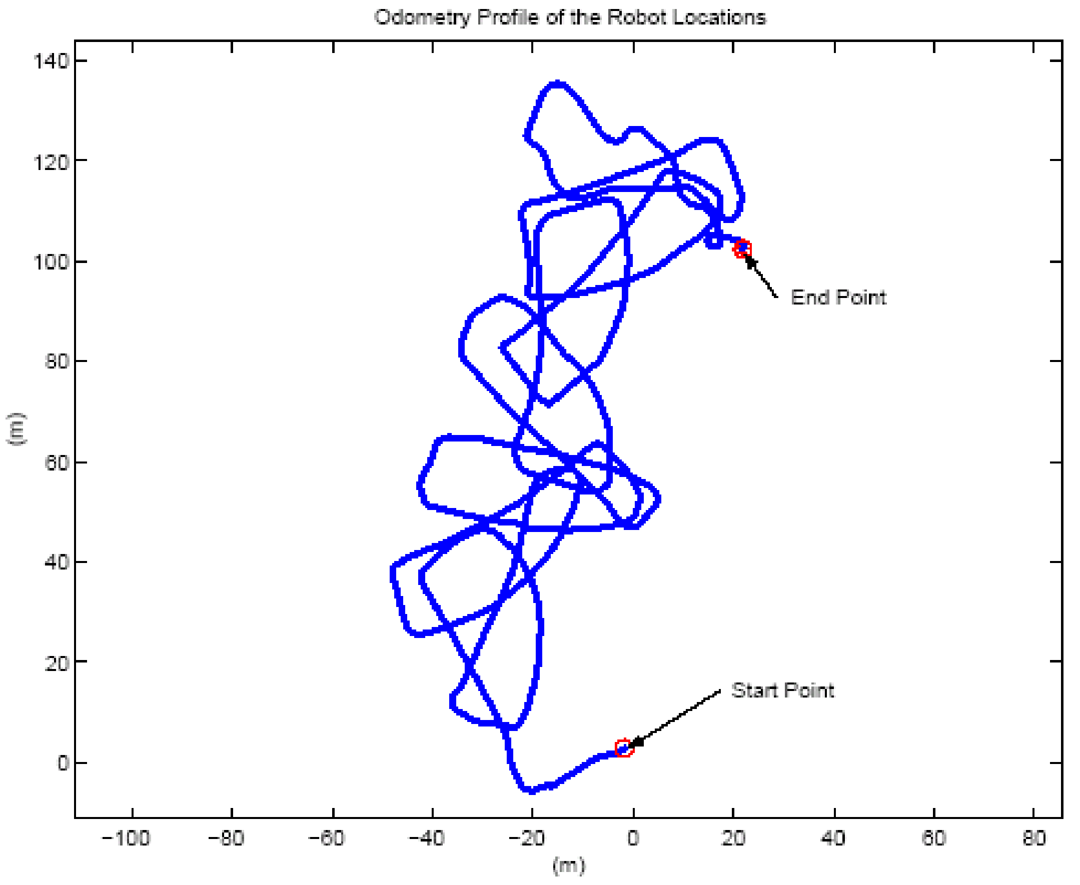


[courtesy by E. Nebot]

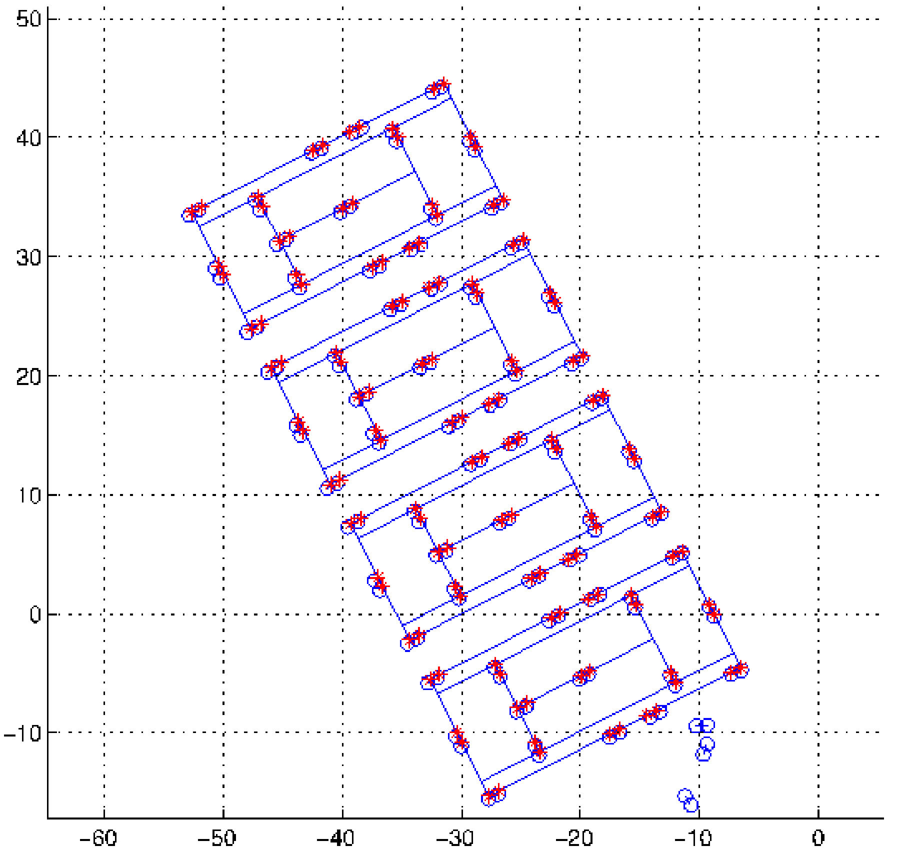
EKF SLAM Application

[courtesy by J. Leonard]

EKF SLAM Application

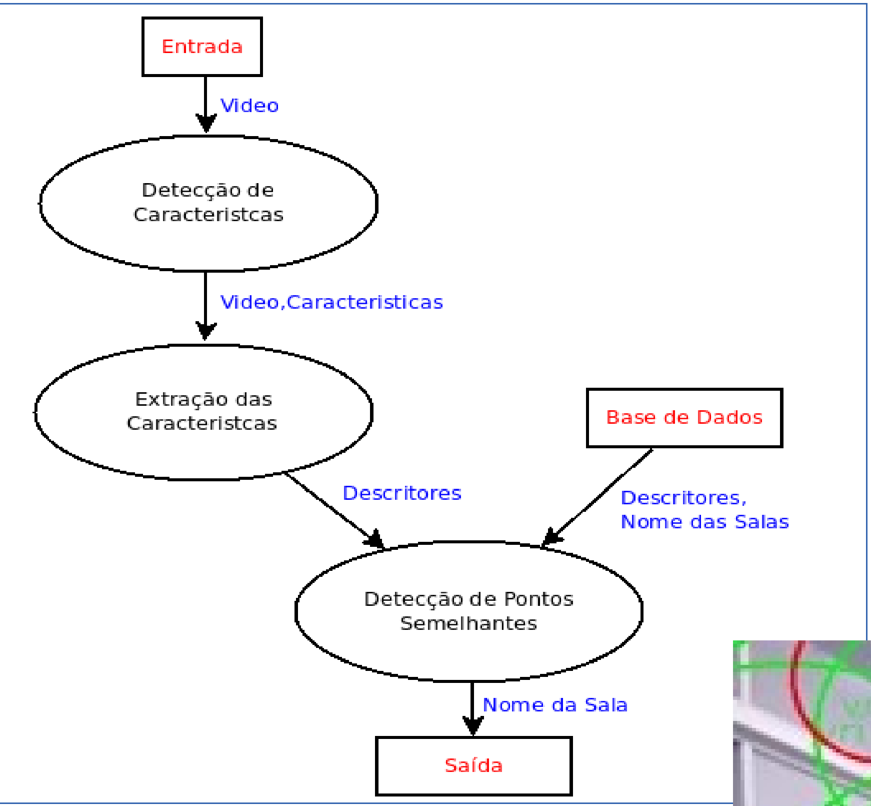


odometry

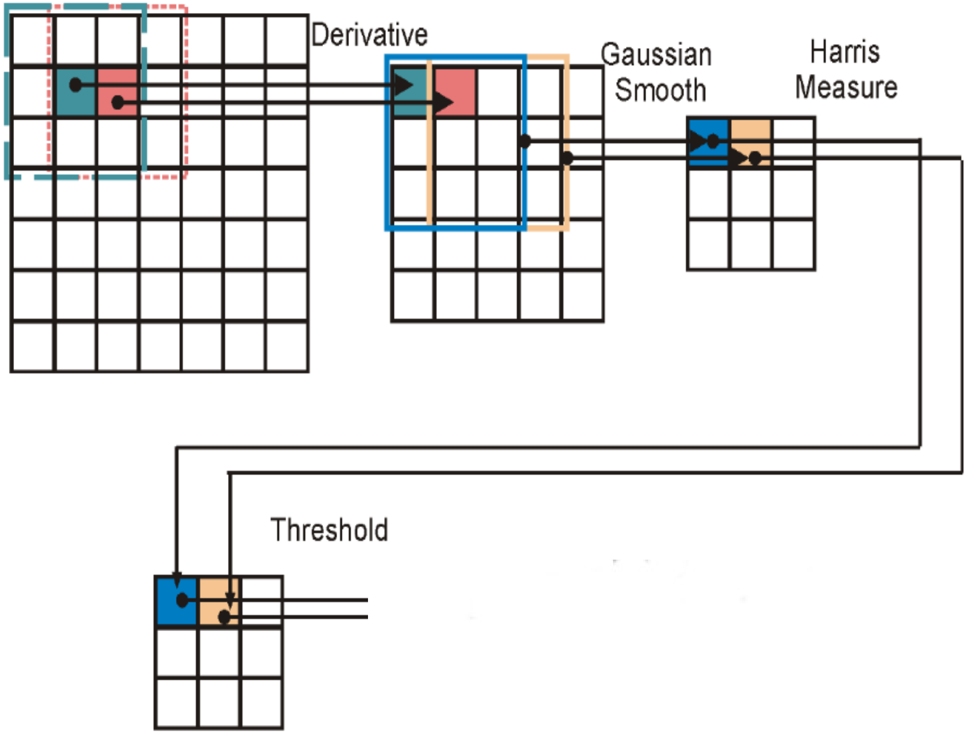


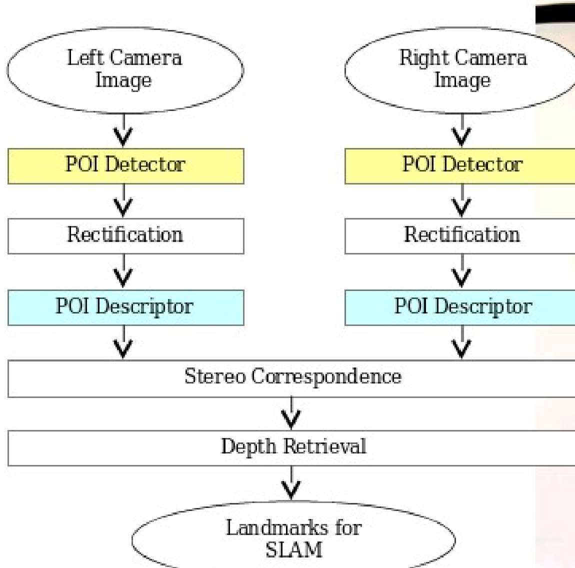
estimated trajectory

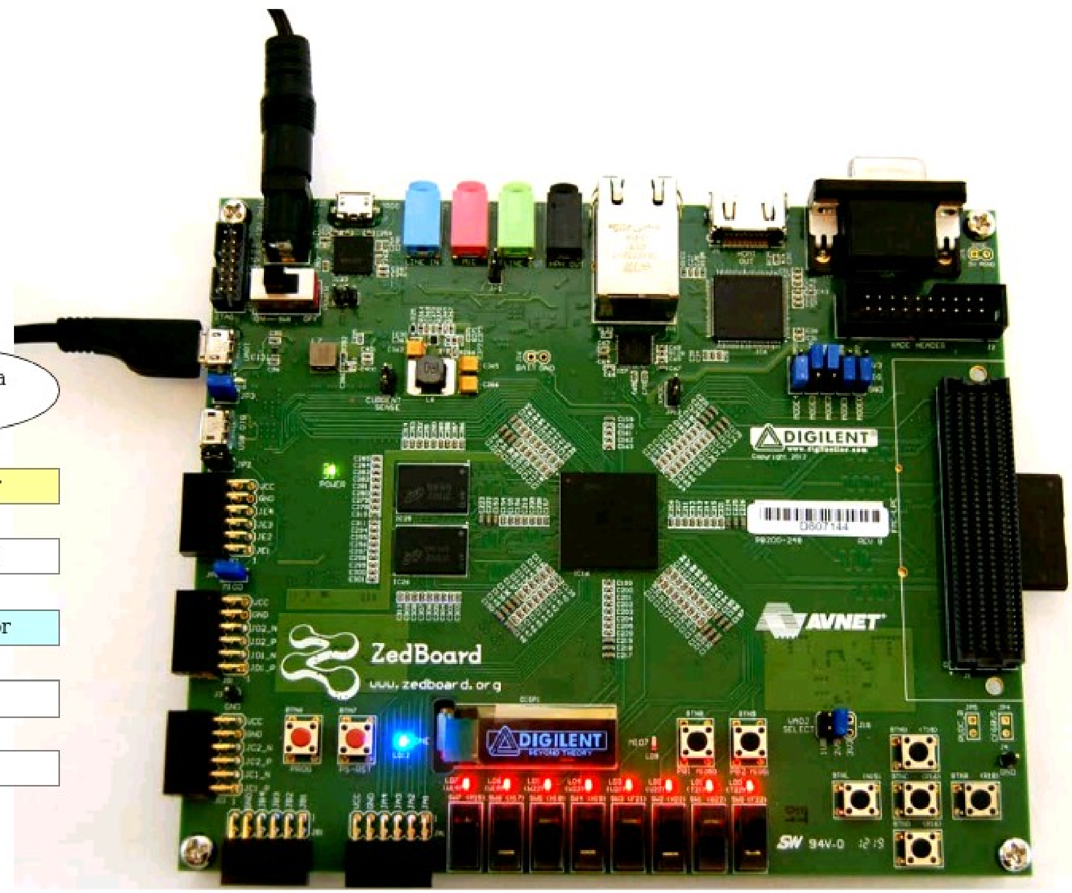
[courtesy by John Leonard]


Entrada
Video
Detecção de Caracteristcas
Video,Caracteristicas
Extração das Caracteristcas
Base de Dados
Descritores
Descritores, Nome das Salas
Detecção de Pontos Semelhantes
Nome da Sala
Saída


VRI:29
Cr:00
Cz:00

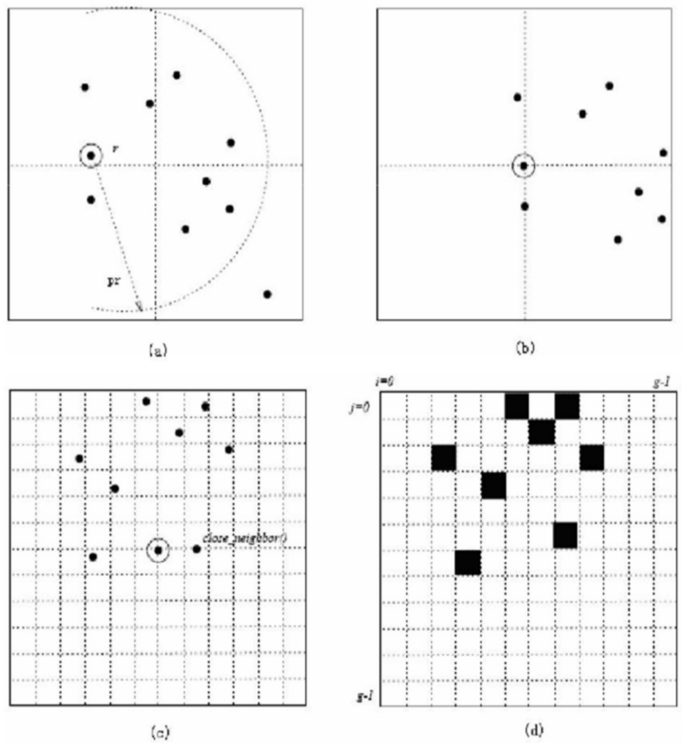

Derivative
Gaussian Smooth
Harris Measure
Threshold


Left Camera Image
Right Camera Image
POI Detector
POI Detector
Rectification
Rectification
POI Descriptor
POI Descriptor
Stereo Correspondence
Depth Retrieval
Landmarks for SLAM


DIGILENT
AVNET
ZedBoard
www.zedboard.org
DIGILENT

Descritor

- Algoritmo Grid

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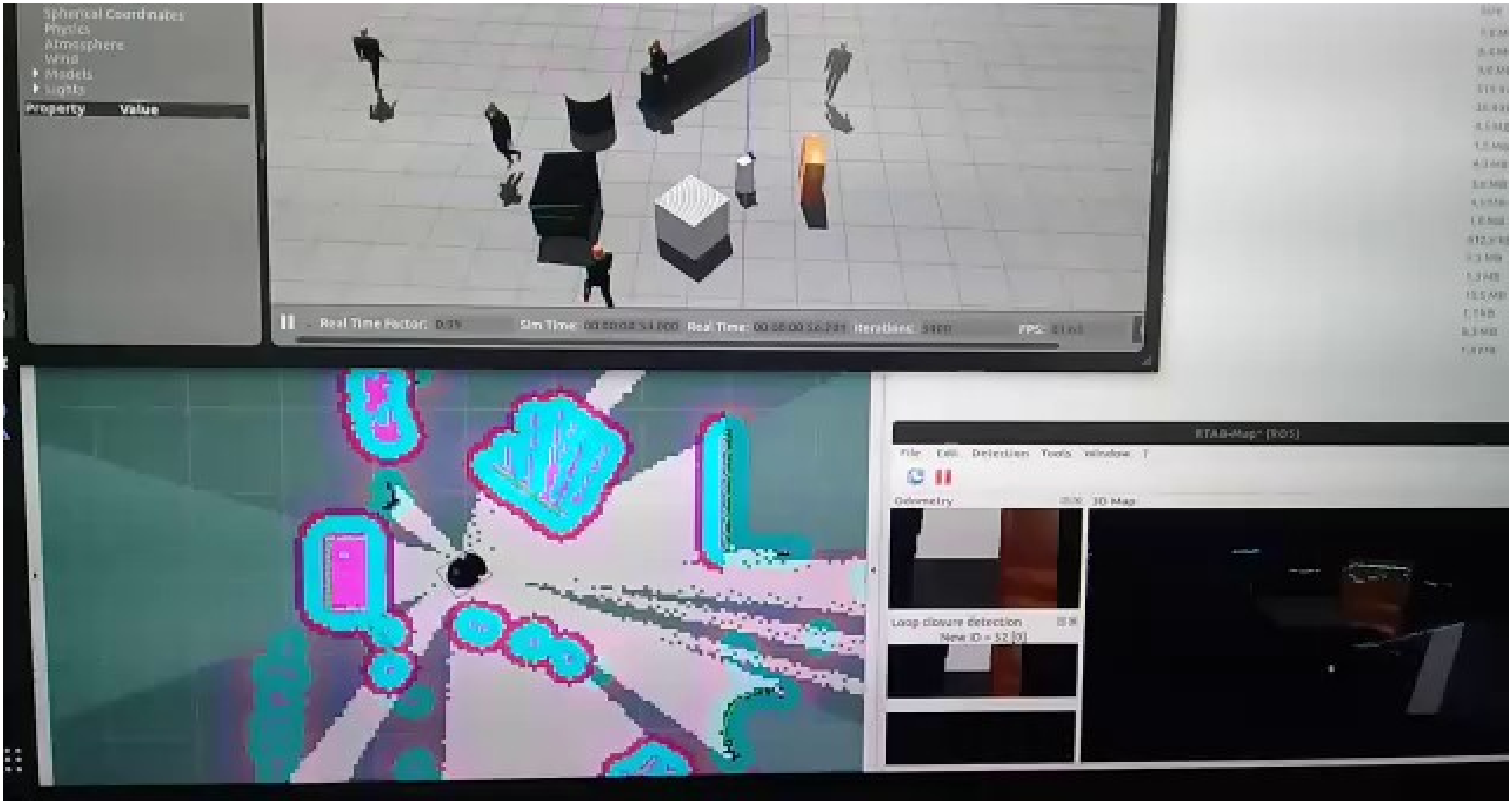
00.00.00.00.00.00.00.00.08
08.00.00.01.01.04.04.00.a0
```

Algoritmo Grid.
(Padgett & KreutzDelgado, 1997)


GEFORCE RTX
SAMSUNG
E2270PV


Spherical Coordinates
Physics
Atmosphere
Wind
Models
Lights
Property
Value
Real Time Factor:
Sim Time:
Real Time:
Iterations:
FPS:
File
Edit
Detection
Tools
Window
Odometry
3D Map
Loop closure detection