ROS-I Basic Training “Mobile Manipulation”

Localisation

M. Stuettgen, N. Limpert

Mobile Autonomous Systems and Cognitive Robotics Institute (MASCOR)

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Overview

- Dealing with Uncertainty
- Pobabilistic Models:
  Hidden Markov Models and Bayes Filter
- Markov Localisation
- Mapping

Learning Objectives

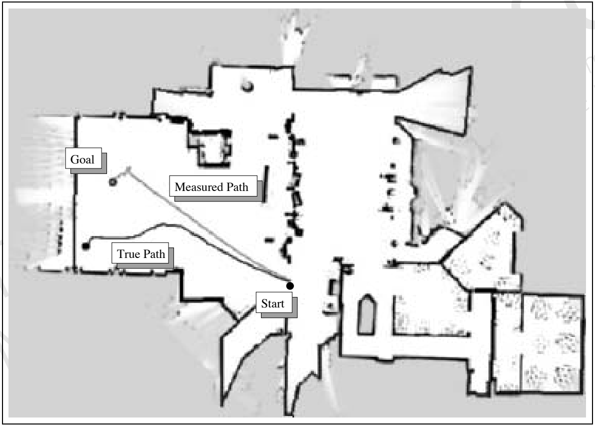
You will

- get to know the basic mathematical foundation underlying probabilistic localisation and mapping.
- learn how to infer the robot's position given a map and regular sensory updates.
- see how a map can be created from sensors input

Outline

- Statistical Background
- Localisation
  - Markov Localisation
  - Grid Localisation
  - Monte Carlo Localisation

Dealing with Uncertainty



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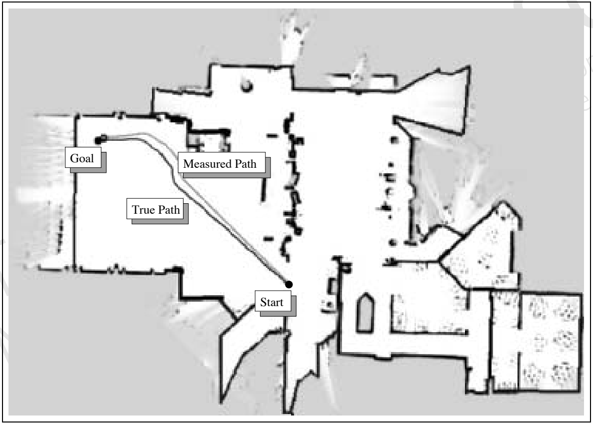
Dealing with Uncertainty



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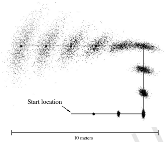
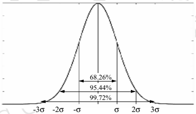
Dealing with Uncertainty

Uncertainty in Actuators



Uncertainty in Sensors



Recall:

Basic Questions

1. Where have I been already?
2. Where am I now?
3. Where am I going?
4. What's the best way to get there?

Problems:

- Localisation
- Mapping

Bayes Filter

```
bayesfilter(Bel(x_{t-1}), z_t, u_t)
begin
    forall the x_t do
        // 1.  Prediction Step
```

$$\overline{bel}(x_t) = \int p(x_t | u_t, x_{t-1}) bel(x_{t-1}) dx_{t-1}$$

```
        // 2.  Correction Step
```

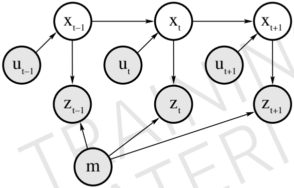
$$bel(x_t) = \eta p(z_t | x_t) \overline{bel}(x_t)$$

```
    end
    return Bel(x_t)
end
```

Outline

- Statistical Background
- Localisation
  - Markov Localisation
  - Grid Localisation
  - Monte Carlo Localisation

Markov Localisation



Source: (Thrun, Burgard, Fox, 2005) ©MIT Press

Integration of a Map

- in sensor model:

$$p(z_t | x_t, m)$$

- in motion model:

$$p(x_t | u_t, x_{t-1}, m)$$

Algorithm: Markov Localisation

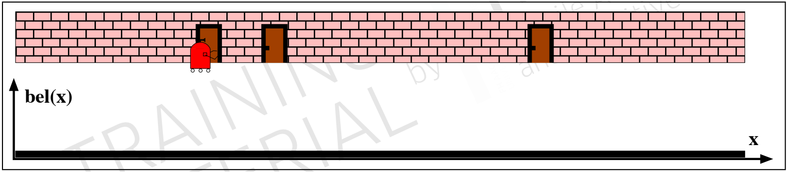
`Markov_localization(`$bel(x_{t-1}), z_t, u_t$`)`
begin
  forall the x_t **do**

$$\overline{bel}(x_t) = \int p(x_t | u_t, x_{t-1}, m) bel(x_{t-1}) dx_{t-1}$$

$$bel(x_t) = \eta p(z_t | x_t, m) \overline{bel}(x_t)$$

  end
  return $bel(x_t)$
end

Markov Localisation



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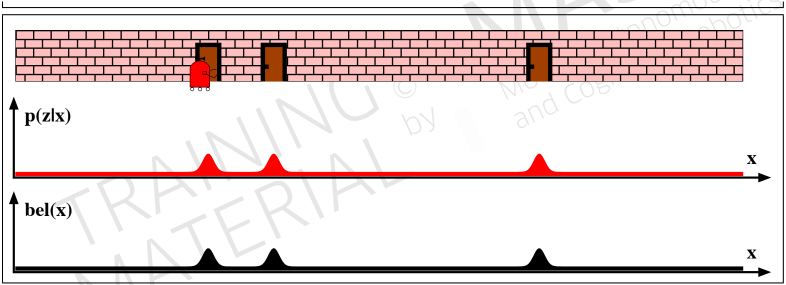
Markov Localisation



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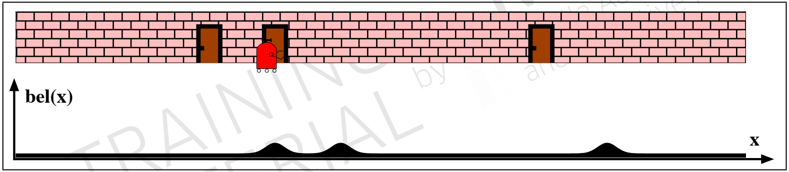
Markov Localisation



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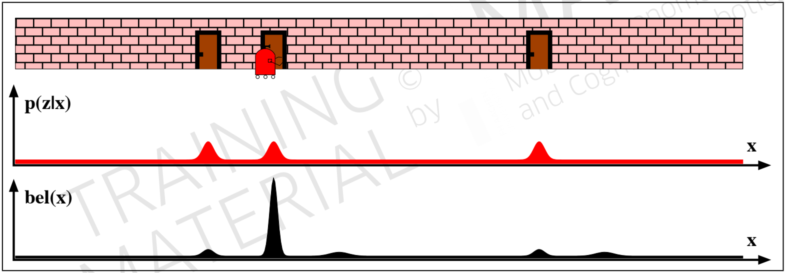
Markov Localisation



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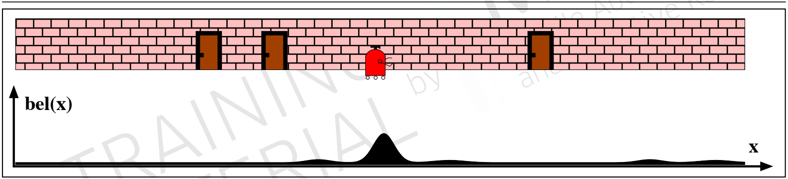
Markov Localisation



Source: (Thrun, Burgard, Fox, 2005) ©MIT Press

Grid Localisation

Idea:
Approximating the a posteriori probabilities by histogram filters (discrete Bayes filter) over cell decomposition of the state space.

The belief is approximated by $bel(x_t) = \{p_{k,t}\}$

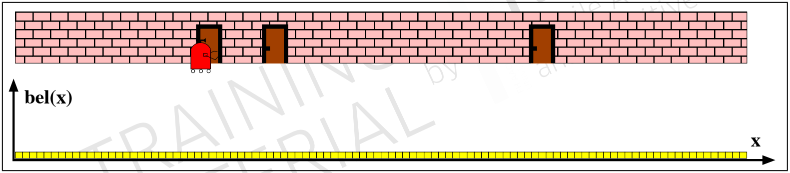
`Discrete_Bayes_filter(`$\{p_{k,t-1}\}, u_t, z_t$`)`
begin
  forall the k **do**

$$\bar{p}_{k,t} = \sum_i p(X_t = x_k | u_t, X_{t-1} = x_t) p_{i,t-1}$$

$$p_{k,t} = \eta p(z_t | X_t = x_k) \bar{p}_{k,t}$$

  end
  return $\{p_{k,t}\}$
end

Grid Localisation



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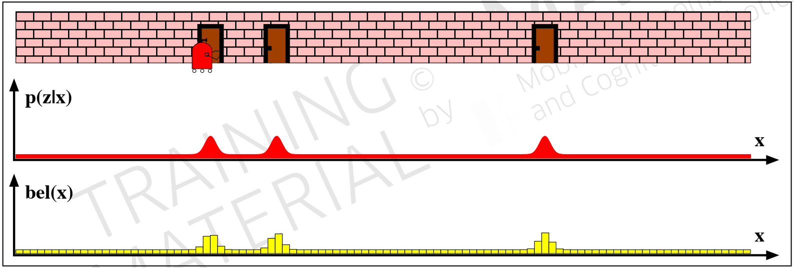
Grid Localisation



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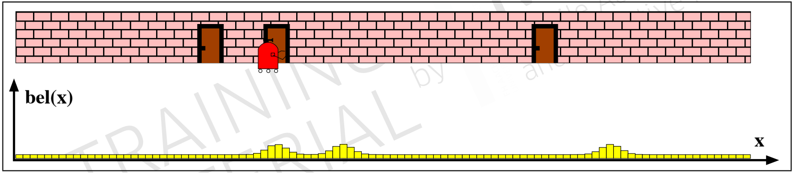
Grid Localisation



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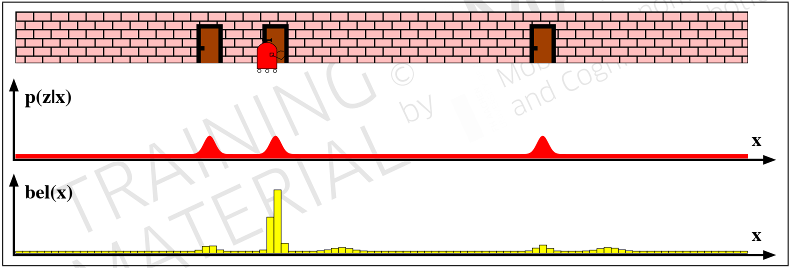
Grid Localisation



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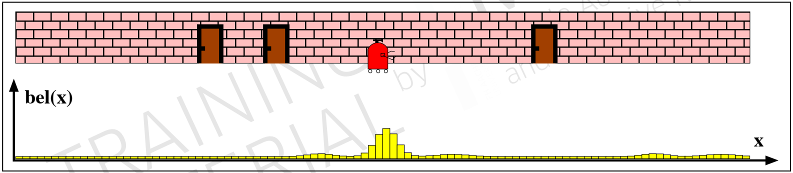
Grid Localisation



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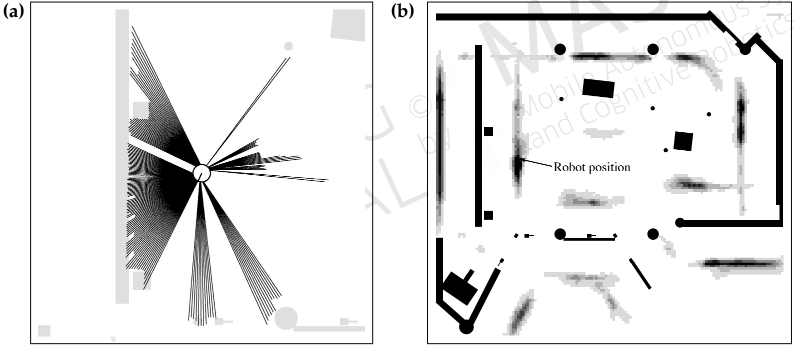
Localisation with LRF



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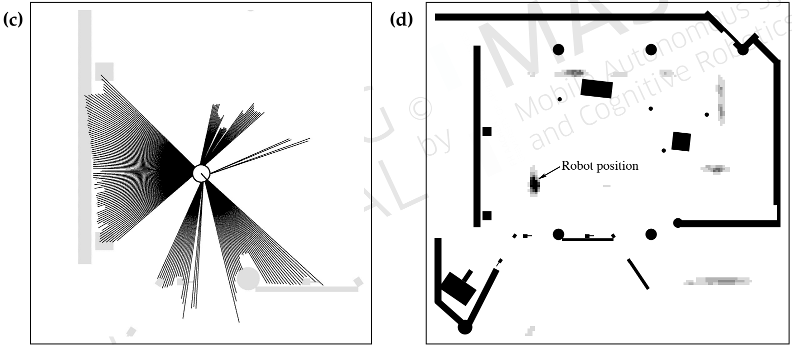
Localisation with LRF



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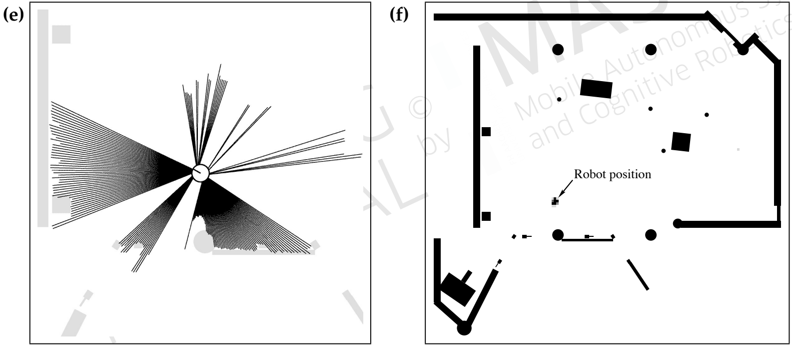
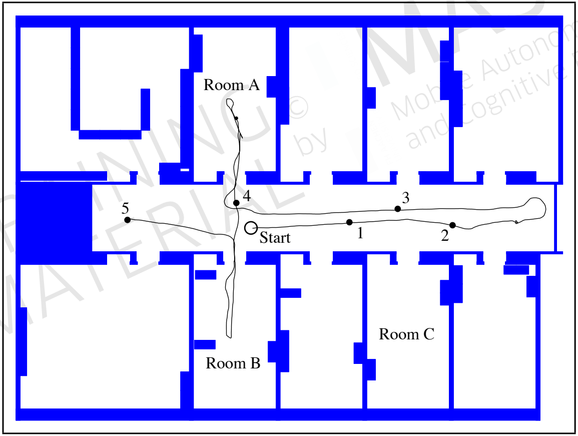
Localisation with LRF



Source: (Thrun, Burgard, Fox, 2005) ©MIT Press

Lokalisation with Sonar (1)

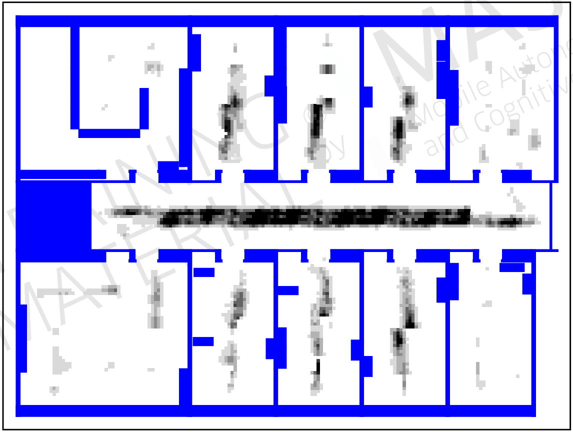
(a) Path and reference poses



Source: (Thrun, Burgard, Fox, 2005) ©MIT Press

Lokalisation with Sonar (1)

(b) Belief at reference pose 1



Source: (Thrun, Burgard, Fox, 2005) ©MIT Press

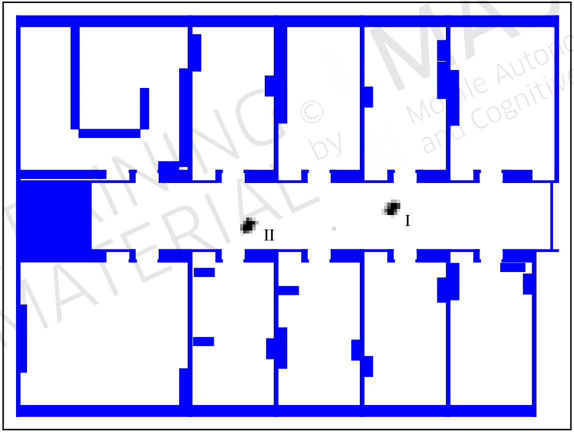
Lokalisation with Sonar (1)

(c) Belief at reference pose 2

Source: (Thrun, Burgard, Fox, 2005) ©MIT Press

Lokalisation with Sonar (1)

(d) Belief at reference pose 3



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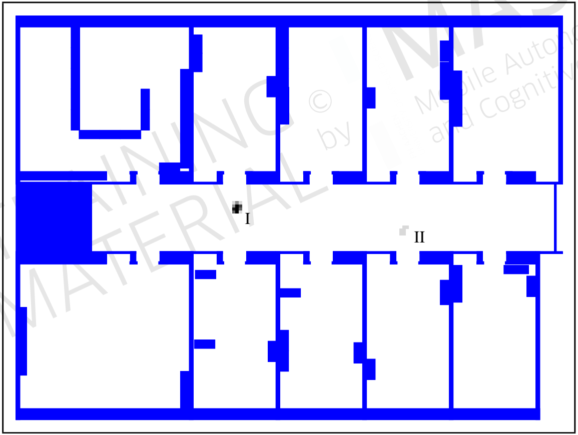
Lokalisation with Sonar (1)

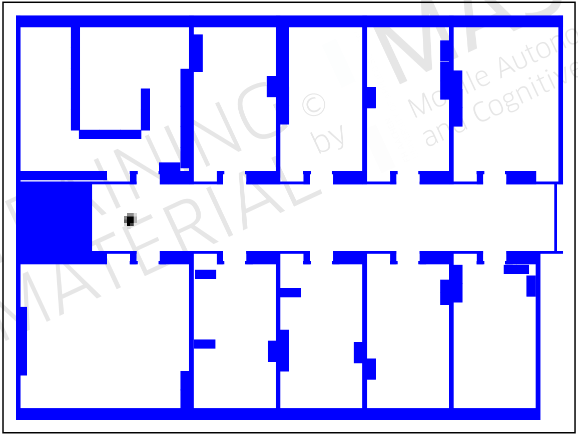
(e) Belief at reference pose 4



Source: (Thrun, Burgard, Fox, 2005) ©MIT Press

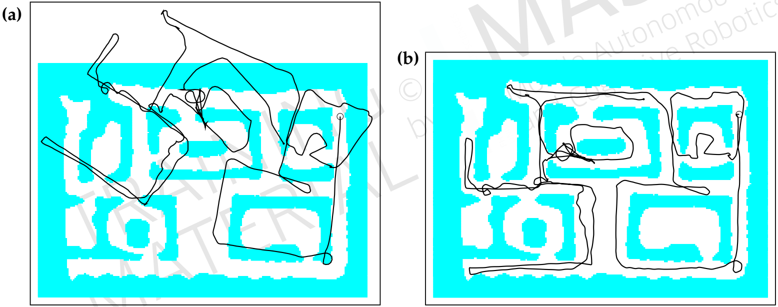
Lokalisation with Sonar (1)

(f) Belief at reference pose 5



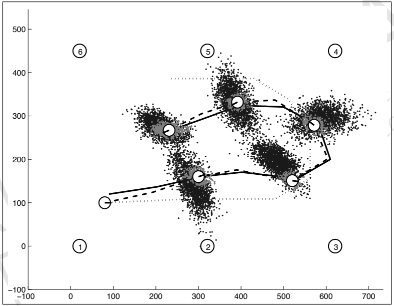
Source: (Thrun, Burgard, Fox, 2005) ©MIT Press

Dead Reckoning vs Grid Localisation



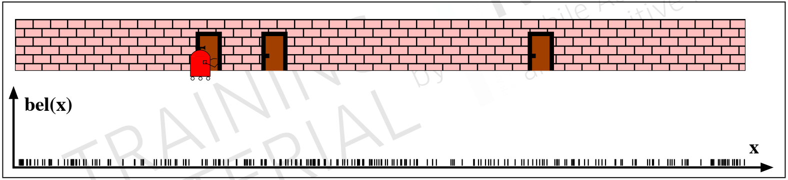
Source: (Thrun, Burgard, Fox, 2005) ©MIT Press

Monte Carlo Localisation



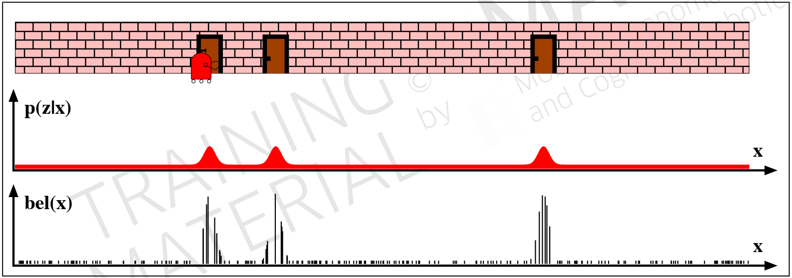
Idea:
The a posteriori distribution $bel(x_t)$ is represented by a set of samples randomly drawn from this distribution.

Monte Carlo Localisation



Source: (Thrun, Burgard, Fox, 2005) ©MIT Press

Monte Carlo Localisation



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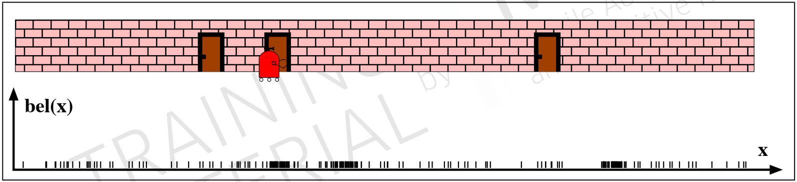
Monte Carlo Localisation



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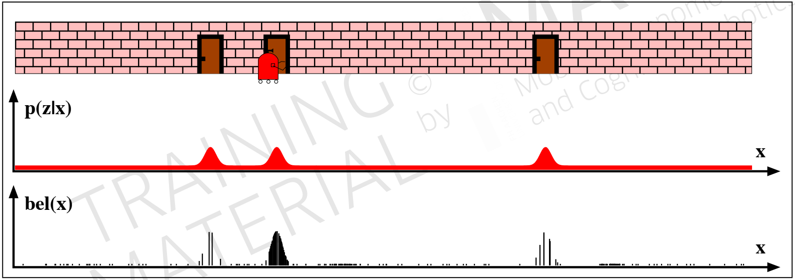
Monte Carlo Localisation



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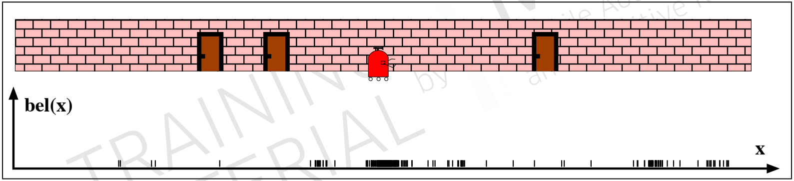
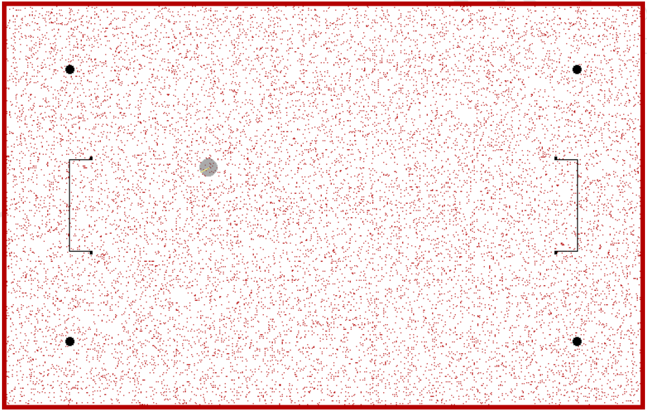
Monte Carlo Localisation



Source: (Thrun, Burgard, Fox, 2005) ©MIT Press

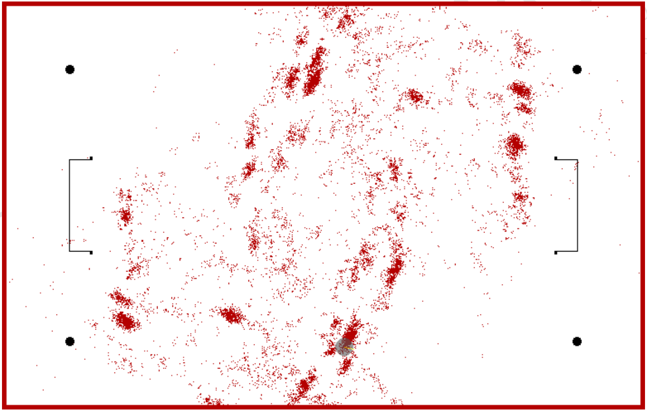
Monte-Carlo-Localisation, Example 1

(Strack, Ferrein, Lakemeyer 2005)



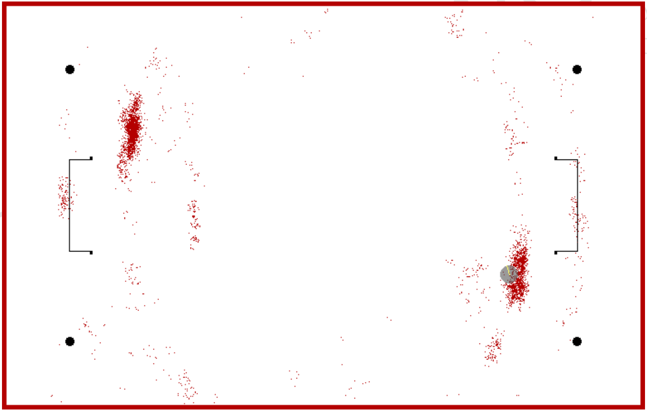
Monte-Carlo-Localisation, Example 1

(Strack, Ferrein, Lakemeyer 2005)



Monte-Carlo-Localisation, Example 1

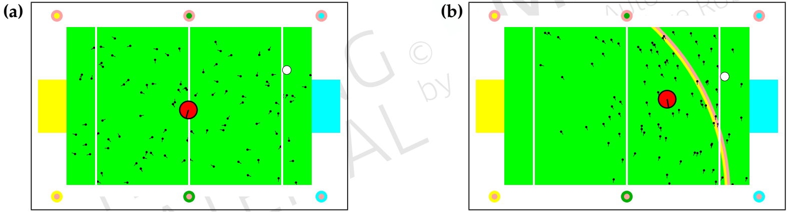
(Strack, Ferrein, Lakemeyer 2005)



Monte-Carlo-Localisation, Example 1

(Strack, Ferrein, Lakemeyer 2005)

Monte-Carlo-Localisation, Example 2



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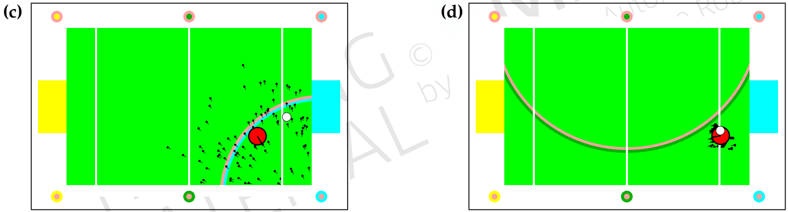
Monte-Carlo-Localisation, Example 2



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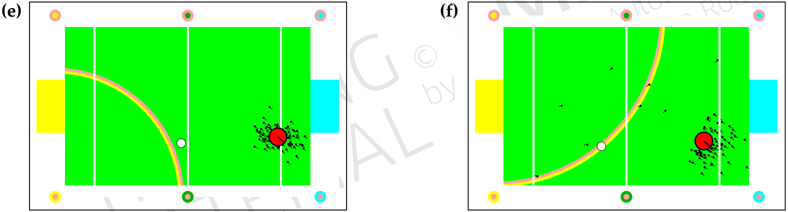
Monte-Carlo-Localisation, Example 2



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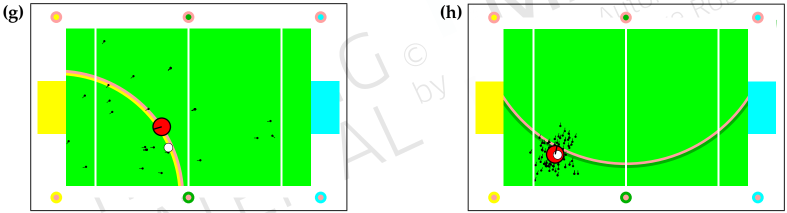
Monte-Carlo-Localisation, Example 2



Source: (Thrun, Burgard, Fox, 2005) ©MIT Press

Summary

- Localisation methods presented today rely on the Bayes filter
- Differences in representing the environment and the way the probability distribution is given.
- Different approaches are differently well-suited for different localisation problems (Tracking, Global, Kidnapped-Robot)
- Depends on robot (accuracy of motion) and sensors used (accuracy of measurement)
- Field of active research; we only saw an excerpt

Learning Objectives

You will learn

- how to set up and use AMCL

Adaptive Monte Carlo Localization - I

- a probabilistic localization system for a robot moving in 2D
- implements the adaptive Monte Carlo localization approach
- uses a particle filter to track the pose of a robot against a known map

http://wiki.ros.org/amcl

Adaptive Monte Carlo Localization - II

subscribes to (default):

- Laser scans : /scan (sensor_msgs/LaserScan)
- Transforms : /tf (tf/tfMessage)
- initial pose : /initialpose (geometry_msgs/PoseWithCovarianceStamped)
- map : /map (nav_msgs/OccupancyGrid)

http://wiki.ros.org/amcl

Adaptive Monte Carlo Localization - III

publishes (default):

- robot's estimated pose in the map, with covariance: /amcl_pose (geometry_msgs/PoseWithCovarianceStamped)
- pose estimates being maintained by the filter: /particlecloud (geometry_msgs/PoseArray)
- the transform from odom : /tf (tf/tfMessage)

http://wiki.ros.org/amcl

Adaptive Monte Carlo Localization - IV

most important parameters (selection):

- ~odom_model_type (string, default: ”diff”)
- ~odom_frame_id (string, default: ”odom”)
- ~base_frame_id (string, default: ”base_link”)
- ~global_frame_id (string, default: ”map”)
- ~min_particles (int, default: 100)
- ~max_particles (int, default: 5000)

http://wiki.ros.org/amcl

Adaptive Monte Carlo Localization - IV

example launchfile:

```
<launch>
<node pkg="amcl" type="amcl" name="amcl" output="screen">
  <param name="odom_model_type" value="diff"/>
  <param name="odom_frame_id" value="odom"/>
  <param name="base_frame_id" value="base_link"/>
  <param name="global_frame_id" value="map"/>
  <remap from="scan" to="laserscan"/>
</node>
</launch>
```

http://wiki.ros.org/amcl

Adaptive Monte Carlo Localization - V

example for high uncertaincy:

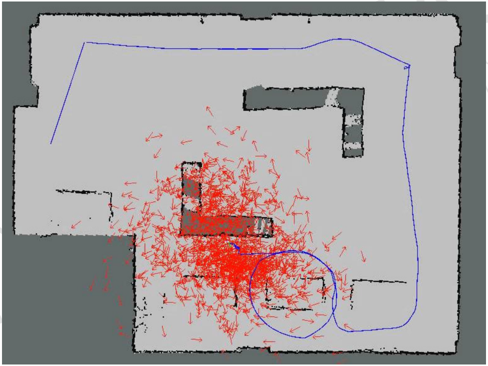


Figure: AMCL high uncertaincy

Adaptive Monte Carlo Localization - VI

example for low uncertaincy:

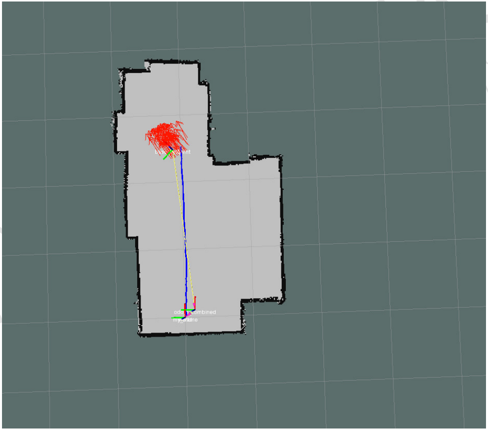


Figure: AMCL low uncertaincy

GMapping - I

- ROS wrapper for OpenSlam's Gmapping
- laser-based SLAM (Simultaneous Localization and Mapping)
- create a 2-D occupancy grid map (like a building floorplan) from laser and pose data collected by a mobile robot

http://wiki.ros.org/gmapping

GMapping - II

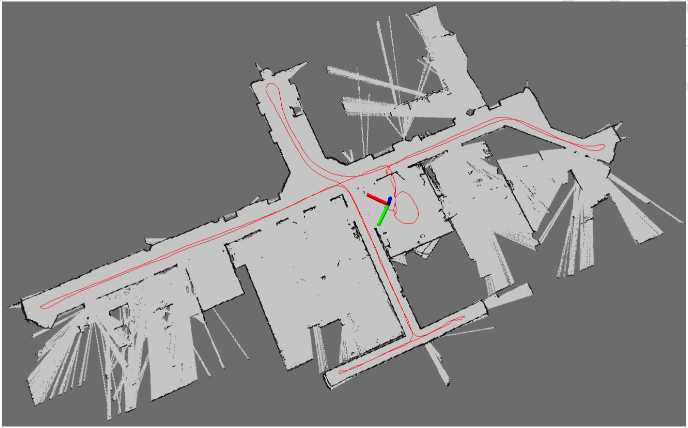


Figure: Example of a ROS Map