ROBOT MAPPING

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Introduction

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Mapping and Localization

Mobile robots are able to navigate through the environment.

In order to perform navigation, robots first need to answer two questions:

- "How does the world look like?"
- "Where am I in this world?"

$\rightarrow$ Solving the two problems in the same time is known as Simultaneous Localization and Mapping **(SLAM)**.

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What is Mapping?

Map = model of the environment

In order to perform mapping, the robot:

- navigates through the workspace.
- collects sensor data (laser scanner, camera).
- fuses the sensor measurements over time.
- generates a map of the environment.

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Why Do Robots Need Mapping?

Autonomous mobile robots perform complex tasks for which detailed information about the environment is required.

Robot mapping is needed for the following tasks:

- localization of the robot in a given map.
- path planning from the current robot position to a goal position in the map.
- autonomous navigation in the environment.

Robot Applications

Mapping is essential for autonomous mobile robotic platforms such as:

- self-driving cars
- automated forklifts in warehouses
- robotic vacuum cleaners
- humanoid robots
- drones etc.

Turtlebot 2

Quadcopter

Pepper Robot

KITTI Vehicle

Types of Maps

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Maps for Human vs. Robot Use

For human purpose, we are used to various types of maps such as:

- Satellite map.
- Geographical maps.
- Political maps.

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Maps for Human vs. Robot Use

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In robotics there are different maps:

- **Grid maps** (show if the environment is free or occupied).
- **Feature maps** (mark the location of obstacles and objects in the world).

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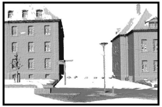
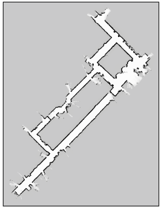
Grid maps

- **Geometric model** of the environment.
- The 2D world plane is divided into **grid cells**.
- Map cells can be **free or occupied**.
- The robot can only navigate in the free cells.
- It is a **dense** representation of the world.
- Suitable for **indoor** environments.





Courtesy: D. Hähnel

Dense grid map.

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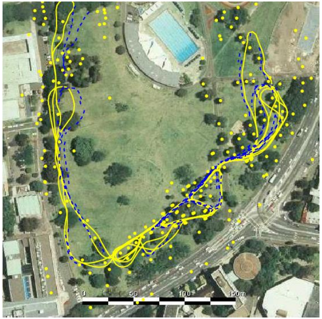
Feature-based maps

- The environment is represented by a set of **observed features**.
- Features are **obstacles** in the world identified by sensor readings (e.g. laser scanner, camera).
- The robot navigates based on the distance and heading w.r.t. the features in the map.
- It is a **sparse** representation of the world.
- Suitable for **outdoor** environments.



Courtesy: E. Nebot

Feature-based map.

Sensors for Mapping

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Types of Mapping

- **Grid mapping**: we can generally use any type of sensor that provides **depth** information about the environment.
- **Feature-based mapping**: we can use sensor data that provides information about the **obstacles** in the world.

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Sensors for Mapping

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Types of Mapping

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Sensors Used

- Proximity sensors:
  - Laser scanner.
  - Ultrasonic sensor.
  - Infrared sensor.
- Stereo vision:
  - Camera.

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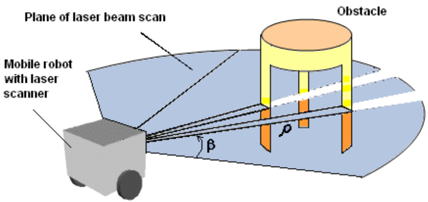
Recap: Phase-based Principle of 2D Laser Scanner

- Sensor emits a continuous laser beam at predefined frequency.
- Rotating mirror shifts the beam with small angle increments.
- Laser beam is reflected back by obstacles.
- Phase shift between emitted and reflected laser beams is proportional to the distance to obstacle.



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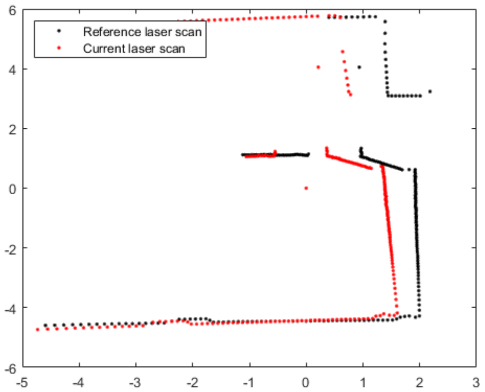
Scan Matching Algorithm

- Incrementally align two consecutive laser scanner measurements.
- Stitch the laser scans to create a map.
- The transformation between two measurements is used in robot localization.
- E.g. Iterative Closest Point.



Scan matching of previous and current laser scan.

Source: `https://www.mathworks.com/help/nav/ug/estimate-robot-pose-with-scan-matching.html`

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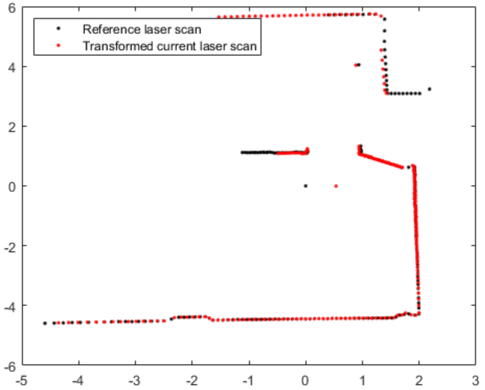
Iterative Closest Point (ICP)

- Minimizes the distance between two point clouds.
- Algorithm:
  1. For each point in the source point cloud, match the closest point in the reference point cloud.
  2. Estimate the combination of rotation and translation between the two point clouds minimizing the root mean square point to point distance.
     Optional: weight points and reject outliers prior to alignment.
  3. Transform the source points using the obtained transformation in Step 2.
  4. Iterate again from Step 1.

Sensors for Mapping



Aligned laser scans using a scan matching algorithm.

Source: `https://www.mathworks.com/help/nav/ug/estimate-robot-pose-with-scan-matching.html`

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Loop Closure

- Loop closing is the task of deciding whether the robot has returned to a previously visited area.
- Used in SLAM to **correct the drift** in mapping and localization.
- Approach: identify features that have been perceived in the past.
- When a match (i.e. loop closure) is detected, update the previous map and position estimates.

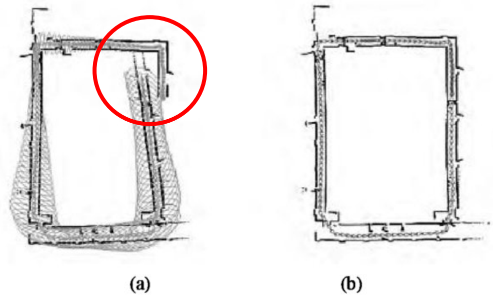


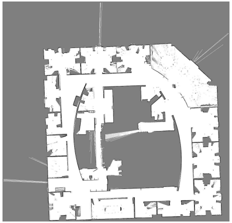
Figure – The role of SLAM loop closure: a) errors increasing before loop closure; b) mapping and localization drift is corrected after closing the loop.

Occupancy Grid Maps

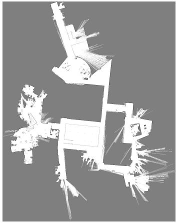
Occupancy Grid Maps

Approach

- Divide the world into grid cells.
- Each cell is either free or occupied.
- Discrete representation of the environment.



Intel Research Lab in Seattle



MIT CSAIL building

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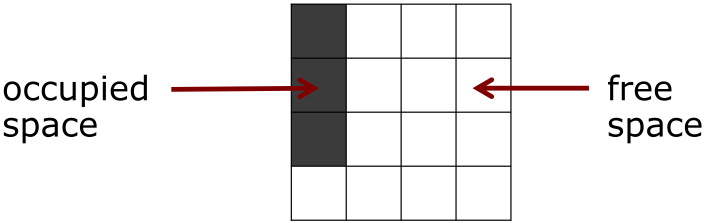
Cell Representation

- Binary cells (either free or occupied).
- Probabilistic cells (certain degree of occupancy).



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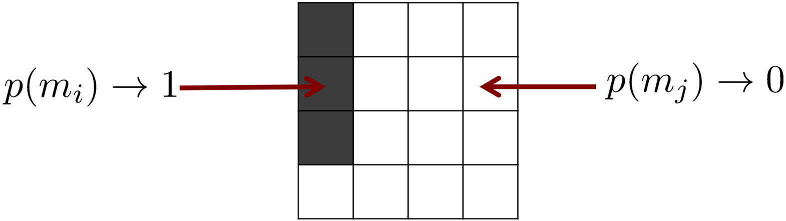
Probabilistic Occupancy

The cell occupancy is modelled by a **binary random variable**.

Map occupancy probabilities:

- Free cell: $p(m_i) = 0$
- Occupied cell: $p(m_i) = 1$
- No knowledge: $p(m_i) = 0.5$



Mapping with Known Poses

Create a map of the environment using:

- Sensor measurements $z_i \rightarrow$ laser scanner.
- Robot poses $x_i \rightarrow$ wheel odometry.

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- Sensor measurements z_i $\rightarrow$ laser scanner.
- Robot poses x_i $\rightarrow$ wheel odometry.

The probability distribution of the map is the product of all individual cell probabilities:

$$p(\boldsymbol{m}|z_{1:t}, x_{1:t}) = \prod_i p(m_i|z_{1:t}, x_{1:t})$$

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Mapping with Known Poses

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Assumptions

- Cells are **independent** of each other.
- Range measurement z_t only depends on current robot pose x_t **(Markov property)**.

Statistics Excursion: Bayes' Theorem

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Bayes' Theorem

- Rule that describes the probability of an event to happen based on previous knowledge of related conditions.
- Remark: probabilities can only take values between 0 and 1.
- Example:

$$P(rain|cloud) = \frac{P(cloud|rain)P(rain)}{P(cloud)}$$

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Bayes' Theorem Formal Definition

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

$P(A|B)$: probability of hypothesis A given data B (**posterior** belief distribution)

$P(B|A)$: likelihood of data B given hypothesis A

$P(A)$: independent probability of hypothesis A (**prior** belief distribution)

$P(B)$: independent probability of data B

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Bayes Filter

- **Bayes Filter**: Probabilistic method to estimate an unknown probability density function (PDF) recursively over time using incoming sensor measurements and a mathematical process model.

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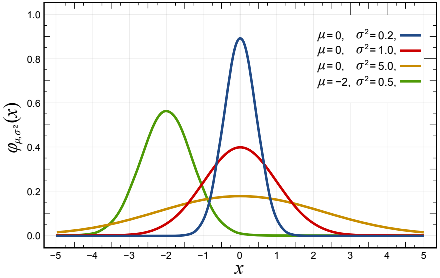

PDF of Gaussian distributions with different mean and variance.

Source: https://en.wikipedia.org/wiki/Normal_distribution.

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Binary Bayes Filter

Let's write the Bayes Filter equation for estimating the cell occupancy probabilities $p(m_i)$ using the Bayes' theorem and Markov property:

$$\frac{p(m_i|z_{1:t}, x_{1:t})}{1 - p(m_i|z_{1:t}, x_{1:t})}$$

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$$= \underbrace{\frac{p(m_i|z_t, x_t)}{1 - p(m_i|z_t, x_t)}}_{\text{new measurement}} \underbrace{\frac{p(m_i|z_{1:t-1}, x_{1:t-1})}{1 - p(m_i|z_{1:t-1}, x_{1:t-1})}}_{\text{recursive term}} \underbrace{\frac{1 - p(m_i)}{p(m_i)}}_{\text{prior}}$$

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Binary Bayes Filter

Apply *log* for easier computations (product becomes sum):

$$\underbrace{l(m_i|z_{1:t}, x_{1:t})}_{\text{posterior}} = \underbrace{l(m_i|z_t, x_t)}_{\textbf{inverse sensor model}} + \underbrace{l(m_i|z_{1:t-1}, x_{1:t-1})}_{\text{recursive term}} - \underbrace{l(m_i)}_{\text{prior}}$$

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Mapping Algorithm

Mapping Algorithm

Occupancy Grid Mapping Algorithm

Algorithm occupancy_grid_mapping($\{l_{t-1,i}\}, x_t, z_t$)**:**

    for all cells $\mathbf{m}_i$ *do*

        if $\mathbf{m}_i$ *in perceptual field of* z_t *then*

            $l_{t,i} = l_{t-1,i} + \textbf{inverse\_sensor\_model}(\mathbf{m}_i, x_t, z_t) - l_0$

        else

            $l_{t,i} = l_{t-1,i}$

        endif

    endfor

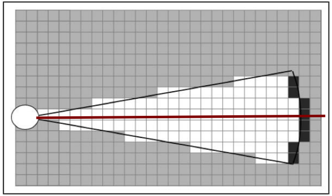
    return $\{l_{t,i}\}$

Binary Bayes' Filter

Source: Probabilistic Robotics, Thrun et al.

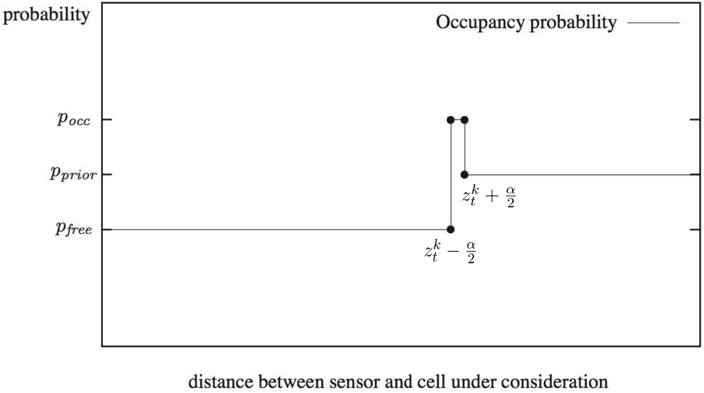
Cell Occupancy

- p_occupied
- p_prior (unchanged)
- p_free



Optical axis of the laser scanner.

Inverse Sensor Model for Laser Scanner



Source: Robot Mapping - Grid Maps Lecture, prof. Burgard, Uni Freiburg.

Mapping Algorithm

Inverse Sensor Model Algorithm

Algorithm inverse_range_sensor_model($\mathbf{m}_i, x_t, z_t$)**:**

    Let x_i, y_i *be the center-of-mass of* $\mathbf{m}_i$
    $r = \sqrt{(x_i - x)^2 + (y_i - y)^2}$
    $\phi = \mathrm{atan2}(y_i - y, x_i - x) - \theta$
    $k = \mathrm{argmin}_j \, |\phi - \theta_{j,\mathrm{sens}}|$
    if $r > \min(z_{\max}, z_t^k + \alpha/2)$ *or* $|\phi - \theta_{k,\mathrm{sens}}| > \beta/2$ *then*
        return l_0
    if $z_t^k < z_{\max}$ *and* $|r - z_t^k| < \alpha/2$
        return l_{occ}
    if $r \leq z_t^k$
        return l_{free}
    endif

Source: Probabilistic Robotics, Thrun et al.

Inverse Sensor Model Algorithm

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 $k = \operatorname{argmin}_j |\phi - \theta_{j,\text{sens}}|$

 if $r > \min(z_{\max}, z_t^k + \alpha/2)$ *or* $|\phi - \theta_{k,\text{sens}}| > \beta/2$ *then*

  return l_0 → prior probability (unchanged)

 if $z_t^k < z_{\max}$ *and* $|r - z_t^k| < \alpha/2$

  return l_{occ} → probability to be occupied

 if $r \leq z_t^k$

  return l_{free} → probability to be free

 endif

Mapping Algorithm

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Parameters

- x_t = robot pose $[x\ y\ \theta]^T$
- x_i, y_i = center coordinates of cell m_i
- r = range of cell m_i (distance from robot)
- ϕ = orientation of cell m_i
- k = laser beam index intersecting cell m_i
- z_t^k = detected range by beam k
- $\theta_{k,sens}$ = orientation of k^{th} laser beam
- α = obstacle thickness
- β = angle increment between scans
- z_{max} = maximum laser measurement range

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Mapping Libraries for ROS2

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1. SLAM Gmapping

- Published by Uni Freiburg (Prof. Wolfram Burgard) in 2007.
- It creates a 2D occupancy grid map from laser range-finder and odometry.
- Posterior distribution estimated using efficient Rao-Blackwellized particle filter.
- Performs loop closure.
- Link: `http://wiki.ros.org/gmapping`

1. SLAM Gmapping

Map properties that can be defined:

- Initial size of the map (x and y in m).
- Resolution of the map (cell size in m).
- Maximum range of the laser scanner measurement.
- Cell occupancy threshold.
- Number of particles. $\rightarrow$ Particle filter in Localization lecture.

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2. Hector SLAM

- Published by TU Darmstadt in 2011.
- It performs fast online learning of occupancy grid maps.
- Low computational resources.
- Uses Lidar and IMU data, but no odometry.
- SLAM without loop closure.
- Link: `http://wiki.ros.org/hector_slam`

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3. Cartographer

- Published by Google Research in 2016.
- It works with a variety of sensor configurations (e.g. Lidar, IMU, cameras).
- It implements the scan matching algorithm.
- It performs local and global SLAM (loop closure).
- Link: `http://wiki.ros.org/cartographer`

4. SLAM Toolbox

- Published by Steve Macenski et al. in 2021 and is currently the supported ROS localization and mapping package.
- Maps large and dynamic spaces.
- Able to continue mapping from prior sessions.
- Implements loop closure.
- Link: `http://wiki.ros.org/slam_toolbox`

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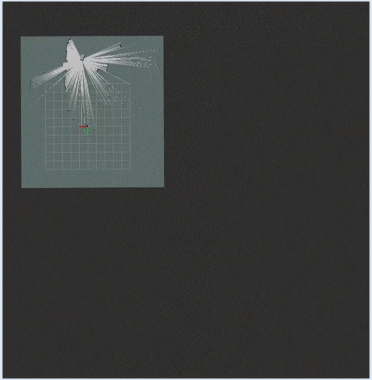
4. SLAM Toolbox



Mapping at the Circuit Launch in Oakland, California.
Source: `https://github.com/SteveMacenski/slam_toolbox`

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Conclusion

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Challenges in Robot Mapping

- Modeling sensor errors.
- Dimension of the environment.
- Data association.
- Multiple sensor modalities.
- Dynamics in the environment.
- Exploration strategy.

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Conclusion

Collaborative Mapping

- Use more robots to explore a larger surface faster.
- Merge the maps generated by multiple robots into a global map.
- Wireless communication for data exchange between robots.

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Collaborative Mapping

- Use more robots to explore a larger surface faster.
- Merge the maps generated by multiple robots into a global map.
- Wireless communication for data exchange between robots.
- Example:
  - ROS package for coordinated multi-robot mapping developed by the University of Klagenfurt, Austria.
  - Tested with Turtlebot (equipped with Kinect sensor) and Pioneer 3-DX (equipped with laser range scanner) robots.

Collaborative Mapping

Coordinated Multi-Robot Exploration: Out of the Box Packages for ROS.
Source: `https://bettstetter.com/collaborative-mapping-with-mobile-robot-teams/`

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Summary

- What is mapping?

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Summary

- What is mapping?
- Types of maps for robotics.

Conclusion

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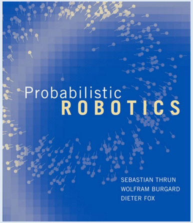
Additional Literature

Probabilistic Robotics, Thrun et al.

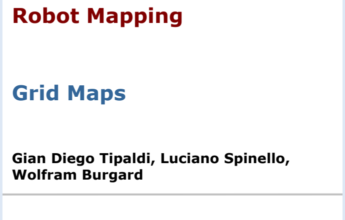
- Chapters 9.1, 9.2.



Source: `https://docs.ufpr.br/~danielsantos/ProbabilisticRobotics.pdf`

Robot Mapping Course, Uni Freiburg

- Occupancy Grid Maps



Source: `http://ais.informatik.uni-freiburg.de/teaching/ws14/mapping/pdf/slam10-gridmaps.pdf`

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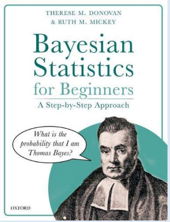
Additional Literature

Bayesian Statistics for Beginners: a step-by-step approach.

- Chapter 3: Bayes' Theorem



Source: https://oxford.universitypressscholarship.com/view/10.1093/oso/9780198841296.001.0001/oso-9780198841296

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Next: Localization.