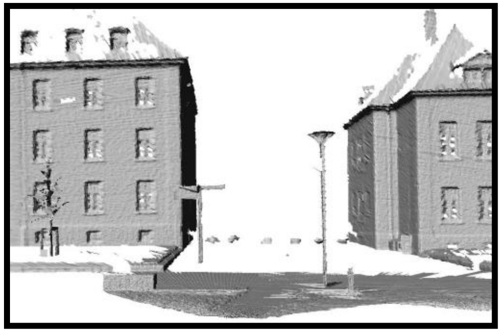
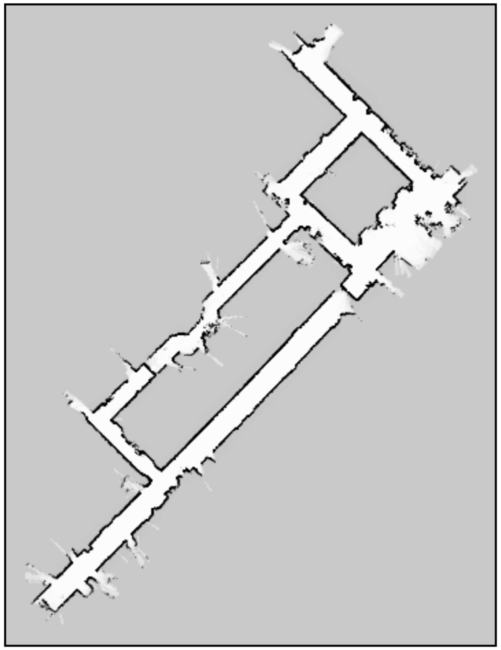
Robot Mapping

Grid Maps

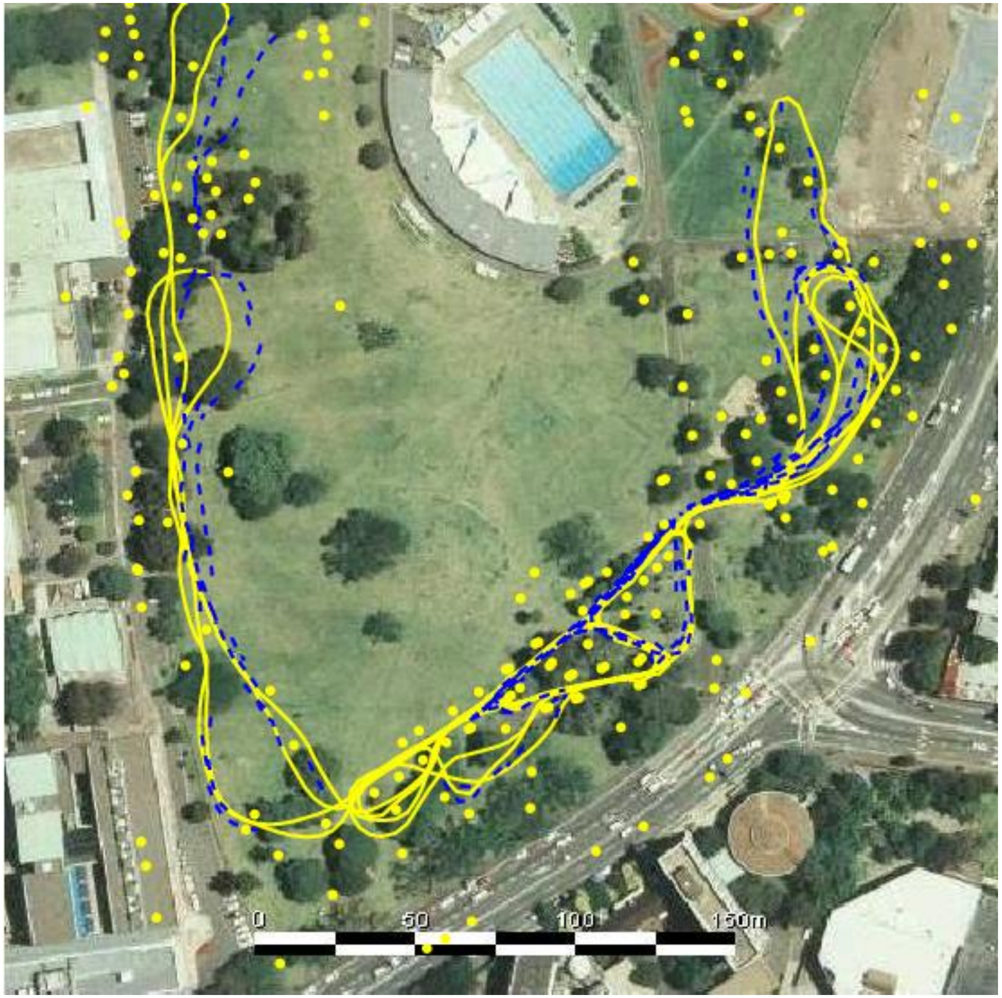
Gian Diego Tipaldi, Wolfram Burgard

Features vs. Volumetric Maps





Courtesy: D. Hähnel



Courtesy: E. Nebot

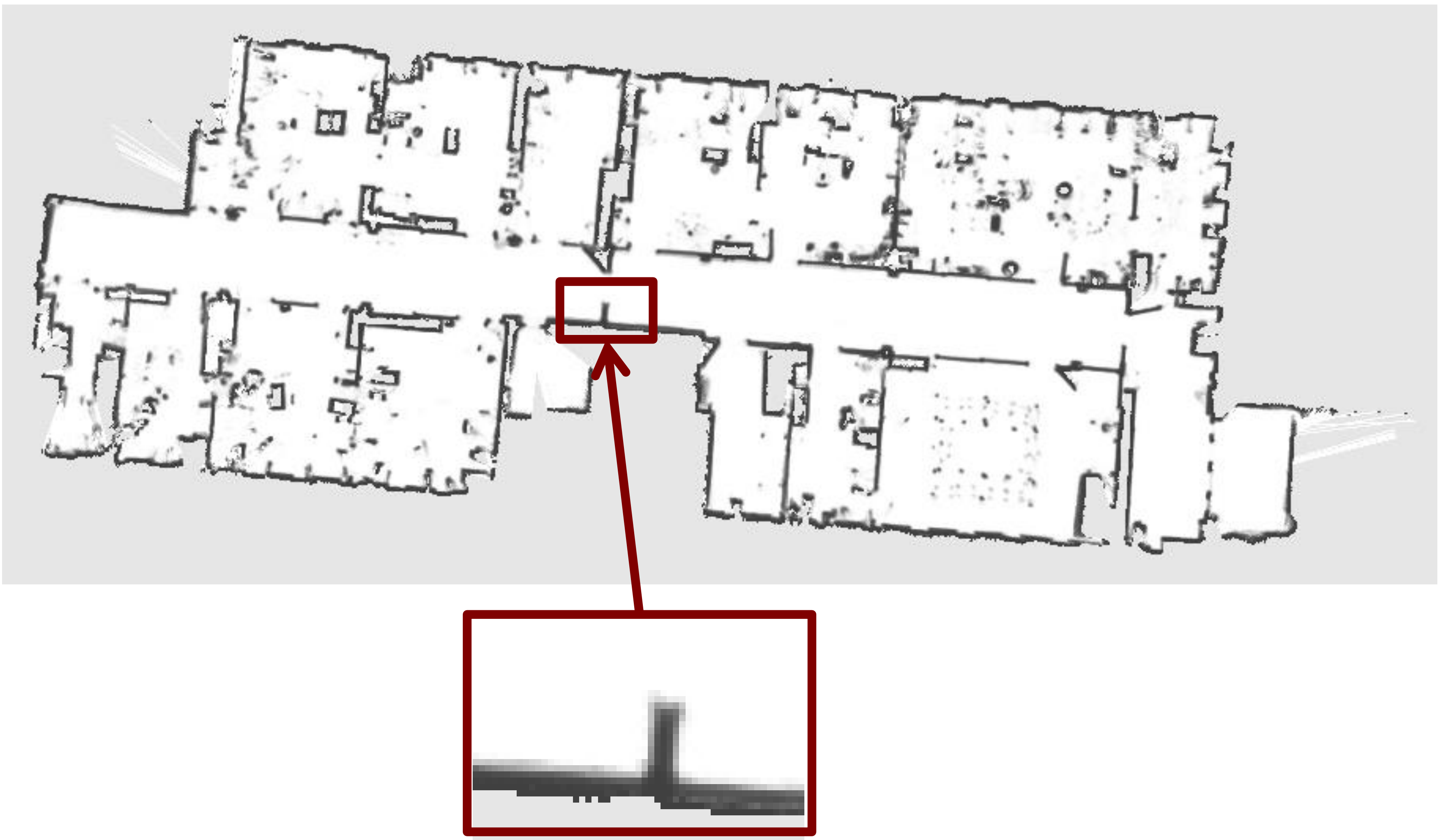
Features

- So far, we only used feature maps
- Natural choice for Kalman filter-based SLAM systems
- Compact representation
- Multiple feature observations improve the landmark position estimate (EKF)

Grid Maps

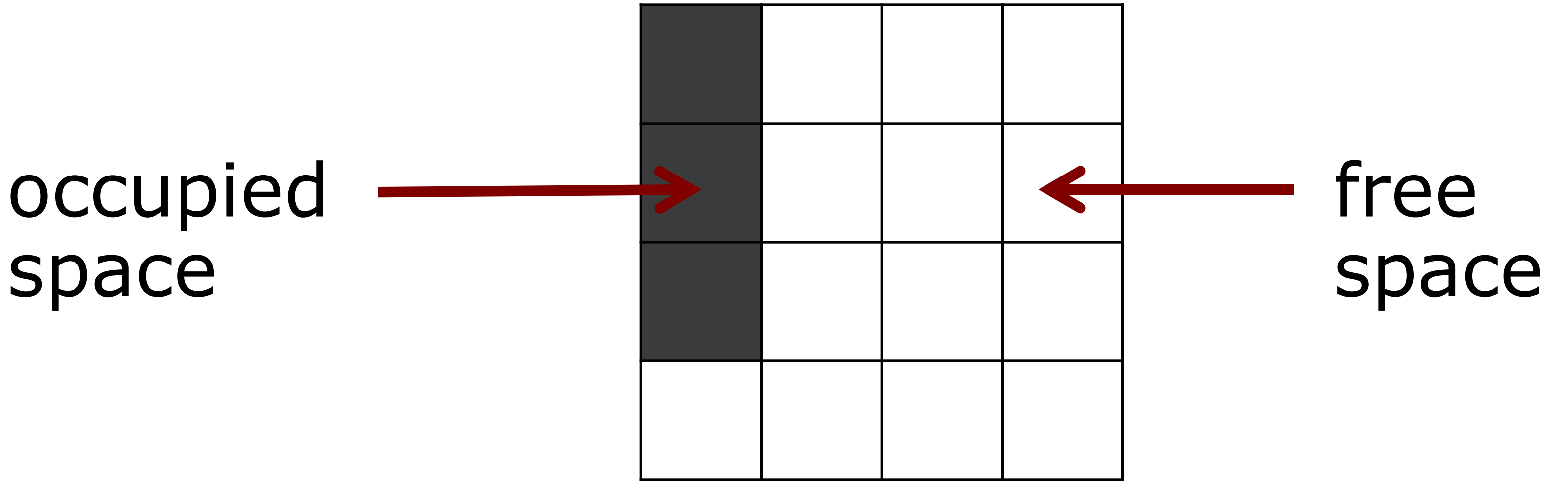
- Discretize the world into cells
- Grid structure is rigid
- Each cell is assumed to be occupied or free space
- Non-parametric model
- Large maps require substantial memory resources
- Do not rely on a feature detector

Example



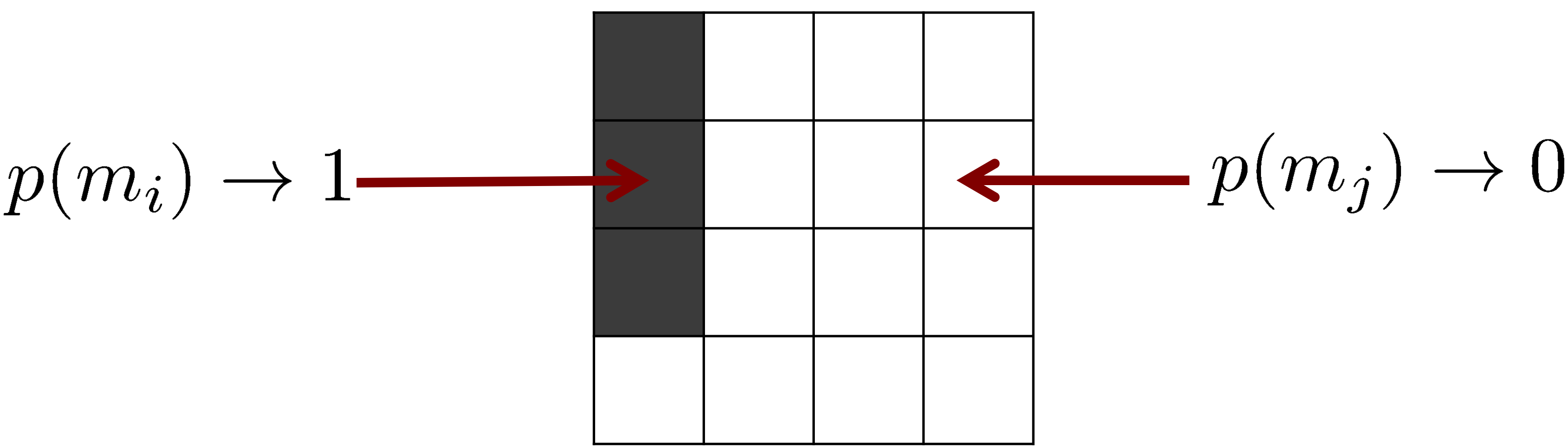
Assumption 1

- The area that corresponds to a cell is either completely free or occupied



Representation

- Each cell is a **binary random variable** that models the occupancy

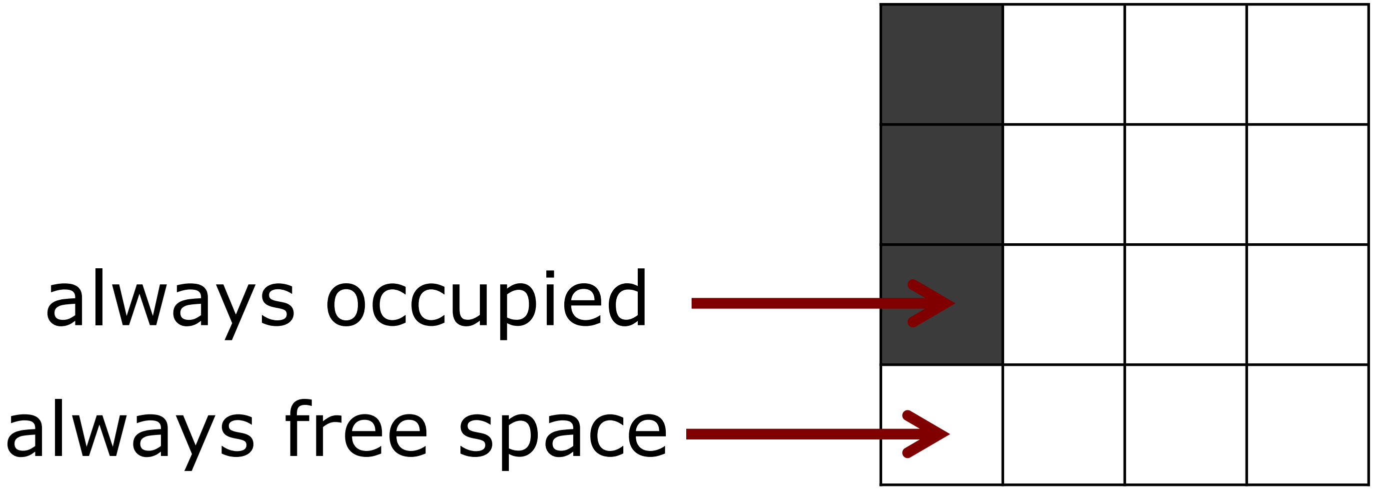


Occupancy Probability

- Each cell is a **binary random variable** that models the occupancy
- Cell is occupied: $p(m_i) = 1$
- Cell is not occupied: $p(m_i) = 0$
- No knowledge: $p(m_i) = 0.5$

Assumption 2

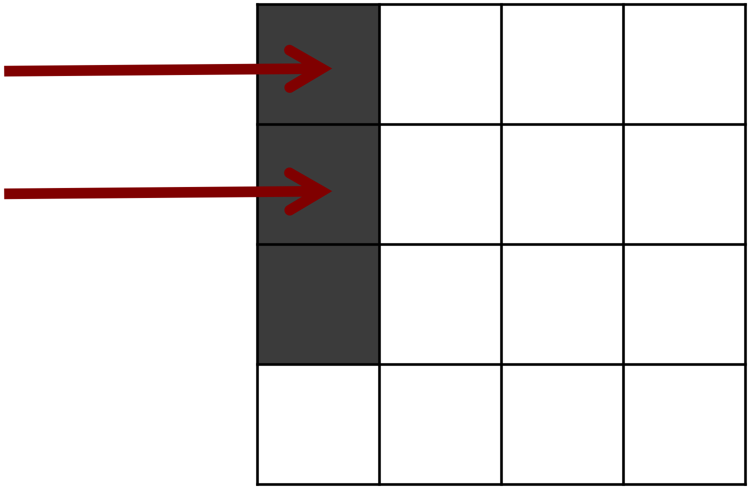
- The world is **static** (most mapping systems make this assumption)



Assumption 3

- The cells (the random variables) are **independent** of each other

no dependency
between the cells



Representation

- The probability distribution of the map is given by the product over the cells

$$p(m) \quad = \quad \prod_i p(m_i)$$

map

cell

Representation

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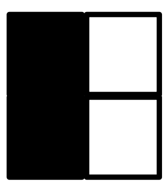
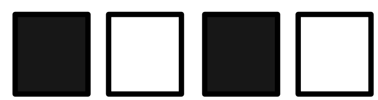
$$p(m) = \prod_i p(m_i)$$



example map
(4-dim state)



4 individual cells

Estimating a Map From Data

- Given sensor data $z_{1:t}$ and the poses $x_{1:t}$ of the sensor, estimate the map

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

binary random variable

Binary Bayes filter
(for a static state)

Static State Binary Bayes Filter

$$p(m_i \mid z_{1:t}, x_{1:t}) \overset{\text{Bayes rule}}{=} \frac{p(z_t \mid m_i, z_{1:t-1}, x_{1:t})\, p(m_i \mid z_{1:t-1}, x_{1:t})}{p(z_t \mid z_{1:t-1}, x_{1:t})}$$

Static State Binary Bayes Filter

$$p(m_i \mid z_{1:t}, x_{1:t}) \overset{\text{Bayes rule}}{=} \frac{p(z_t \mid m_i, z_{1:t-1}, x_{1:t})\, p(m_i \mid z_{1:t-1}, x_{1:t})}{p(z_t \mid z_{1:t-1}, x_{1:t})}$$

$$\overset{\text{Markov}}{=} \frac{p(z_t \mid m_i, x_t)\, p(m_i \mid z_{1:t-1}, x_{1:t-1})}{p(z_t \mid z_{1:t-1}, x_{1:t})}$$

Static State Binary Bayes Filter

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$$p(z_t \mid m_i, x_t) \overset{\text{Bayes rule}}{=} \frac{p(m_i \mid z_t, x_t)\, p(z_t \mid x_t)}{p(m_i \mid x_t)}$$

Static State Binary Bayes Filter

$$
\begin{aligned}
p(m_i \mid z_{1:t}, x_{1:t}) &\overset{\text{Bayes rule}}{=} \frac{p(z_t \mid m_i, z_{1:t-1}, x_{1:t})\; p(m_i \mid z_{1:t-1}, x_{1:t})}{p(z_t \mid z_{1:t-1}, x_{1:t})} \\
&\overset{\text{Markov}}{=} \frac{p(z_t \mid m_i, x_t)\; p(m_i \mid z_{1:t-1}, x_{1:t-1})}{p(z_t \mid z_{1:t-1}, x_{1:t})} \\
&\overset{\text{Bayes rule}}{=} \frac{p(m_i \mid z_t, x_t)\; p(z_t \mid x_t)\; p(m_i \mid z_{1:t-1}, x_{1:t-1})}{p(m_i \mid x_t)\; p(z_t \mid z_{1:t-1}, x_{1:t})}
\end{aligned}
$$

Static State Binary Bayes Filter

$$
\begin{aligned}
p(m_i \mid z_{1:t}, x_{1:t}) &\overset{\text{Bayes rule}}{=} \frac{p(z_t \mid m_i, z_{1:t-1}, x_{1:t})\; p(m_i \mid z_{1:t-1}, x_{1:t})}{p(z_t \mid z_{1:t-1}, x_{1:t})} \\
&\overset{\text{Markov}}{=} \frac{p(z_t \mid m_i, x_t)\; p(m_i \mid z_{1:t-1}, x_{1:t-1})}{p(z_t \mid z_{1:t-1}, x_{1:t})} \\
&\overset{\text{Bayes rule}}{=} \frac{p(m_i \mid z_t, x_t)\; p(z_t \mid x_t)\; p(m_i \mid z_{1:t-1}, x_{1:t-1})}{p(m_i \mid x_t)\; p(z_t \mid z_{1:t-1}, x_{1:t})} \\
&\overset{\text{indep.}}{=} \frac{p(m_i \mid z_t, x_t)\; p(z_t \mid x_t)\; p(m_i \mid z_{1:t-1}, x_{1:t-1})}{p(m_i)\; p(z_t \mid z_{1:t-1}, x_{1:t})}
\end{aligned}
$$

Static State Binary Bayes Filter

$$p(m_i \mid z_{1:t}, x_{1:t}) \overset{\text{Bayes rule}}{=} \frac{p(z_t \mid m_i, z_{1:t-1}, x_{1:t})\; p(m_i \mid z_{1:t-1}, x_{1:t})}{p(z_t \mid z_{1:t-1}, x_{1:t})}$$

$$\overset{\text{Markov}}{=} \frac{p(z_t \mid m_i, x_t)\; p(m_i \mid z_{1:t-1}, x_{1:t-1})}{p(z_t \mid z_{1:t-1}, x_{1:t})}$$

$$\overset{\text{Bayes rule}}{=} \frac{p(m_i \mid z_t, x_t)\; p(z_t \mid x_t)\; p(m_i \mid z_{1:t-1}, x_{1:t-1})}{p(m_i \mid x_t)\; p(z_t \mid z_{1:t-1}, x_{1:t})}$$

$$\overset{\text{indep.}}{=} \frac{p(m_i \mid z_t, x_t)\; p(z_t \mid x_t)\; p(m_i \mid z_{1:t-1}, x_{1:t-1})}{p(m_i)\; p(z_t \mid z_{1:t-1}, x_{1:t})}$$

Do exactly the same for the opposite event:

$$p(\neg m_i \mid z_{1:t}, x_{1:t}) \overset{\text{the same}}{=} \frac{p(\neg m_i \mid z_t, x_t)\; p(z_t \mid x_t)\; p(\neg m_i \mid z_{1:t-1}, x_{1:t-1})}{p(\neg m_i)\; p(z_t \mid z_{1:t-1}, x_{1:t})}$$

Static State Binary Bayes Filter

- By computing the ratio of both probabilities, we obtain:

$$\frac{p(m_i \mid z_{1:t}, x_{1:t})}{p(\neg m_i \mid z_{1:t}, x_{1:t})} = \frac{\frac{p(m_i|z_t,x_t)\,\cancel{p(z_t|x_t)}\,p(m_i|z_{1:t-1},x_{1:t-1})}{p(m_i)\,\cancel{p(z_t|z_{1:t-1},x_{1:t})}}}{\frac{p(\neg m_i|z_t,x_t)\,\cancel{p(z_t|x_t)}\,p(\neg m_i|z_{1:t-1},x_{1:t-1})}{p(\neg m_i)\,\cancel{p(z_t|z_{1:t-1},x_{1:t})}}}$$

Static State Binary Bayes Filter

- By computing the ratio of both probabilities, we obtain:

$$\frac{p(m_i \mid z_{1:t}, x_{1:t})}{p(\neg m_i \mid z_{1:t}, x_{1:t})}$$

$$= \frac{p(m_i \mid z_t, x_t)\, p(m_i \mid z_{1:t-1}, x_{1:t-1})\, p(\neg m_i)}{p(\neg m_i \mid z_t, x_t)\, p(\neg m_i \mid z_{1:t-1}, x_{1:t-1})\, p(m_i)}$$

$$= \frac{p(m_i \mid z_t, x_t)}{1 - p(m_i \mid z_t, x_t)} \frac{p(m_i \mid z_{1:t-1}, x_{1:t-1})}{1 - p(m_i \mid z_{1:t-1}, x_{1:t-1})} \frac{1 - p(m_i)}{p(m_i)}$$

Static State Binary Bayes Filter

- By computing the ratio of both probabilities, we obtain:

$$
\begin{aligned}
&\frac{p(m_i \mid z_{1:t}, x_{1:t})}{1 - p(m_i \mid z_{1:t}, x_{1:t})} \\
&\quad = \frac{p(m_i \mid z_t, x_t)\; p(m_i \mid z_{1:t-1}, x_{1:t-1})\; p(\neg m_i)}{p(\neg m_i \mid z_t, x_t)\; p(\neg m_i \mid z_{1:t-1}, x_{1:t-1})\; p(m_i)} \\
&\quad = \underbrace{\frac{p(m_i \mid z_t, x_t)}{1 - p(m_i \mid z_t, x_t)}}_{\text{uses } z_t} \underbrace{\frac{p(m_i \mid z_{1:t-1}, x_{1:t-1})}{1 - p(m_i \mid z_{1:t-1}, x_{1:t-1})}}_{\text{recursive term}} \underbrace{\frac{1 - p(m_i)}{p(m_i)}}_{\text{prior}}
\end{aligned}
$$

From Ratio to Probability

- We can easily turn the ration into the probability

$$
\begin{aligned}
\frac{p(x)}{1-p(x)} &= Y \\
p(x) &= Y - Y\,p(x) \\
p(x)\,(1+Y) &= Y \\
p(x) &= \frac{Y}{1+Y} \\
p(x) &= \frac{1}{1+\frac{1}{Y}}
\end{aligned}
$$

From Ratio to Probability

- Using $p(x) = \left[1 + Y^{-1}\right]^{-1}$ directly leads to

$$
\begin{aligned}
& p(m_i \mid z_{1:t}, x_{1:t}) \\
= \quad & \left[1 + \frac{1 - p(m_i \mid z_t, x_t)}{p(m_i \mid z_t, x_t)} \frac{1 - p(m_i \mid z_{1:t-1}, x_{1:t-1})}{p(m_i \mid z_{1:t-1}, x_{1:t-1})} \frac{p(m_i)}{1 - p(m_i)}\right]^{-1}
\end{aligned}
$$

For reasons of efficiency, one performs the calculations in the log odds notation

Log Odds Notation

- The log odds notation computes the logarithm of the ratio of probabilities

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

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

$$\Rightarrow \quad l(m_i \mid z_{1:t}, x_{1:t}) = \log \left(\frac{p(m_i \mid z_{1:t}, x_{1:t})}{1 - p(m_i \mid z_{1:t}, x_{1:t})} \right)$$

Log Odds Notation

- Log odds ratio is defined as

$$l(x) \quad = \quad \log \frac{p(x)}{1 - p(x)}$$

- and with the ability to retrieve $p(x)$

$$p(x) \quad = \quad 1 - \frac{1}{1 + \exp l(x)}$$

Occupancy Mapping in Log Odds Form

- The product turns into a sum

$$
\begin{aligned}
& l(m_i \mid z_{1:t}, x_{1:t}) \\
&= \quad \underbrace{l(m_i \mid z_t, x_t)}_{\text{inverse sensor model}} + \underbrace{l(m_i \mid z_{1:t-1}, x_{1:t-1})}_{\text{recursive term}} - \underbrace{l(m_i)}_{\text{prior}}
\end{aligned}
$$

- or in short

$$
l_{t,i} \quad = \quad \text{inv\_sensor\_model}(m_i, x_t, z_t) + l_{t-1,i} - l_0
$$

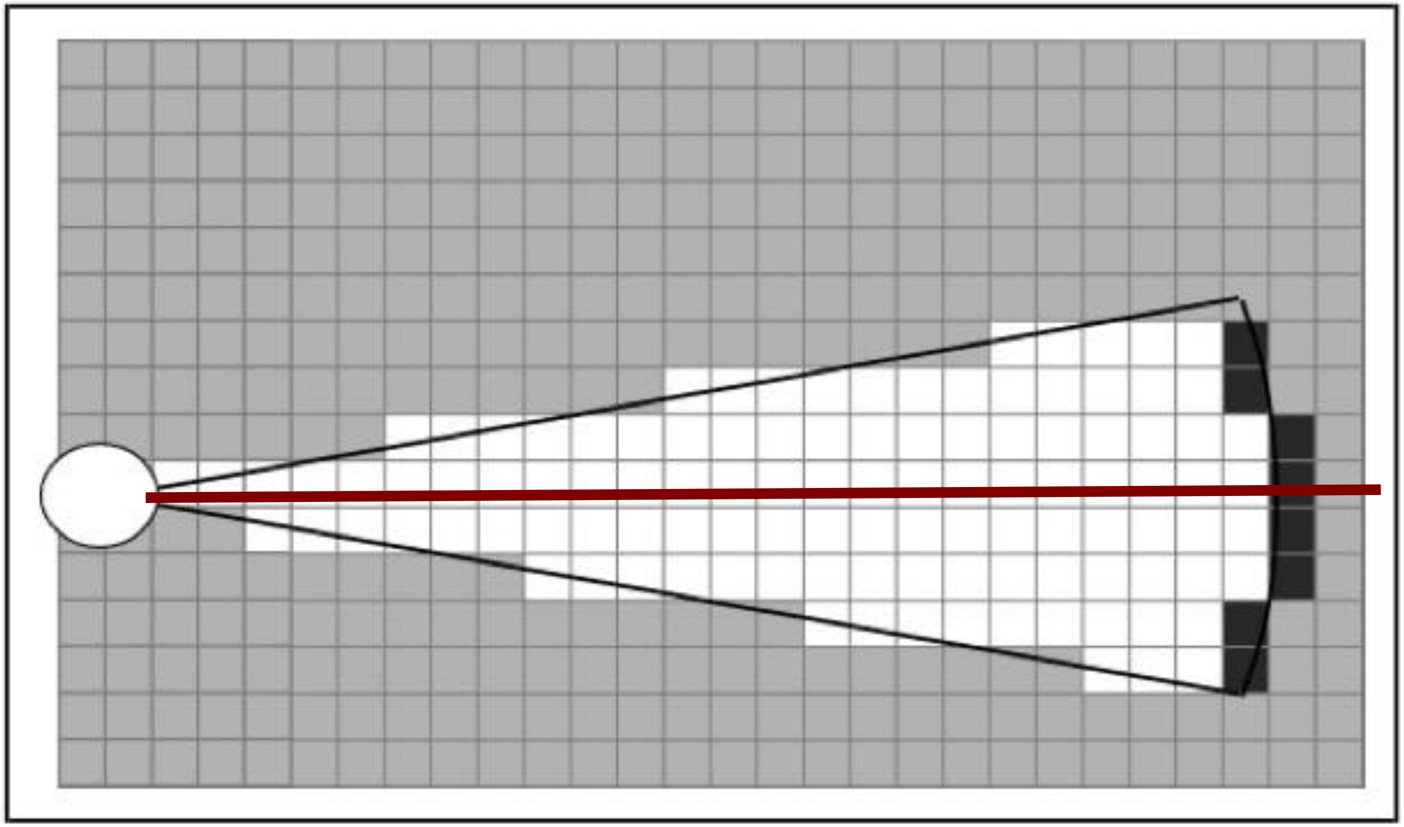
Occupancy Mapping Algorithm

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

for all cells m_i do
    if m_i in perceptual field of z_t then
        $l_{t,i} = l_{t-1,i} + \text{inv\_sensor\_model}(m_i, x_t, z_t) - l_0$
    else
        $l_{t,i} = l_{t-1,i}$
    endif
endfor
return $\{l_{t,i}\}$

highly efficient, we only have to compute sums

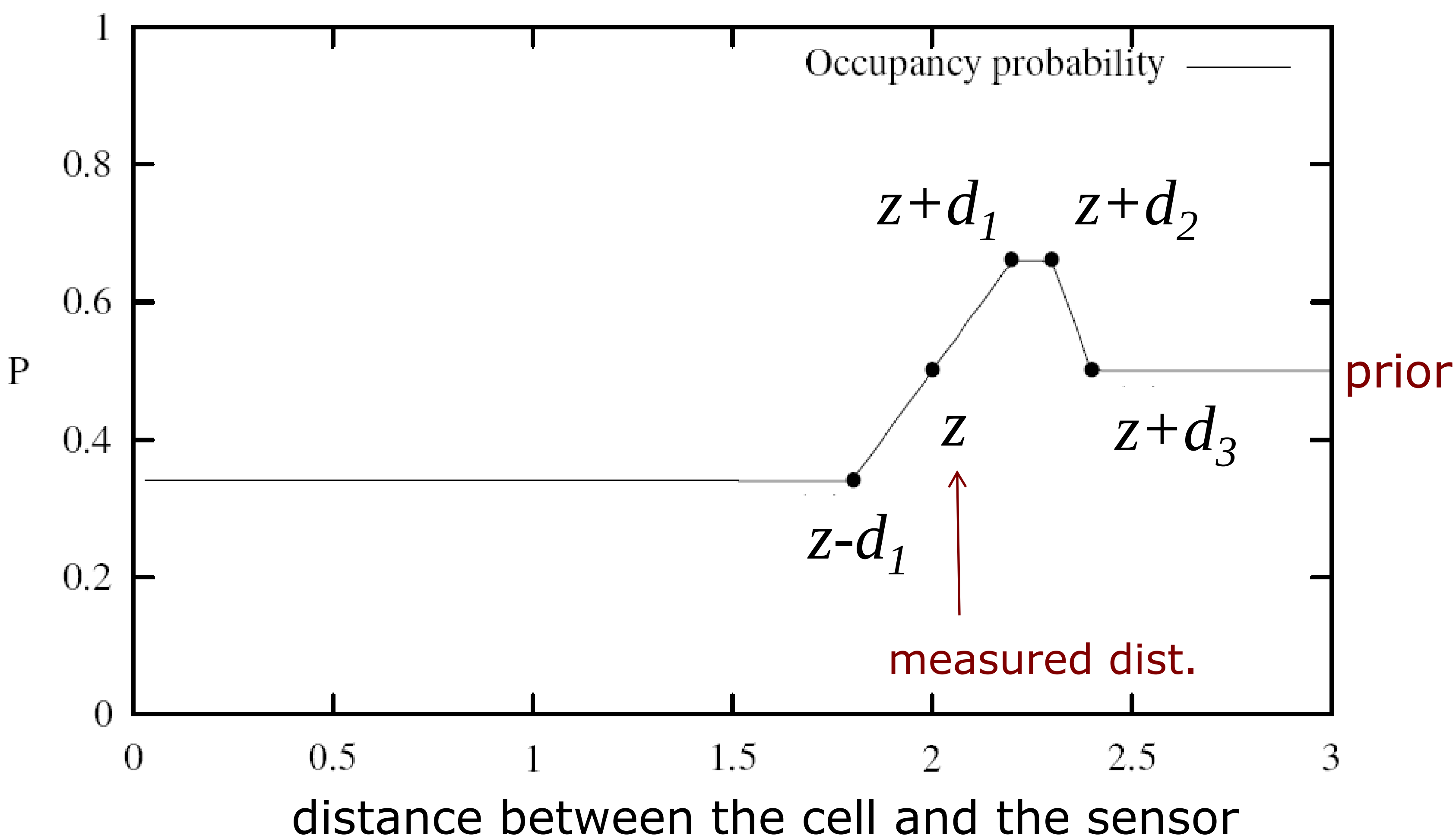
Inverse Sensor Model for Sonar Range Sensors



In the following, consider the cells along the optical axis (red line)

Courtesy: Thrun, Burgard, Fox

Occupancy Value Depending on the Measured Distance



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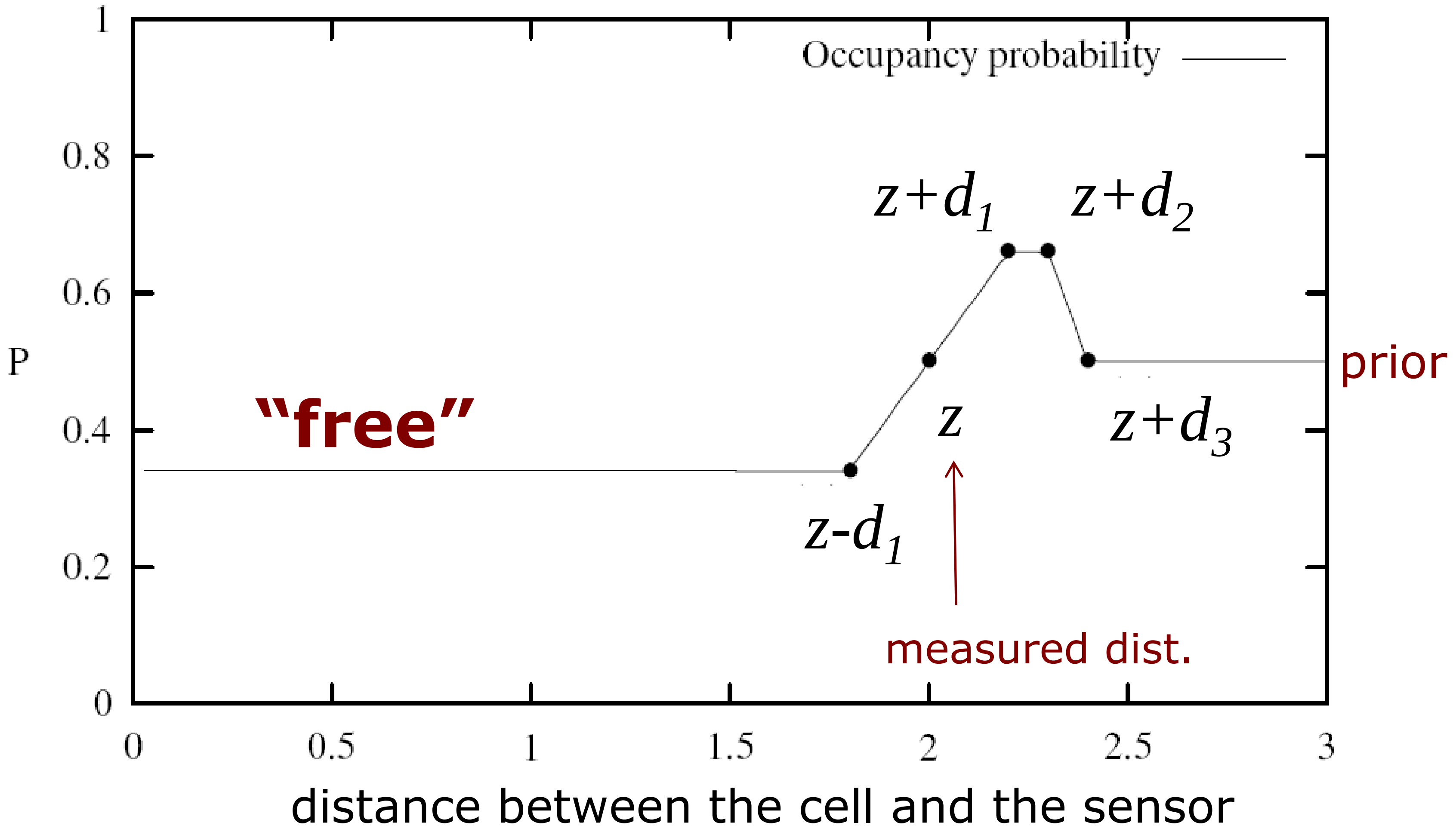
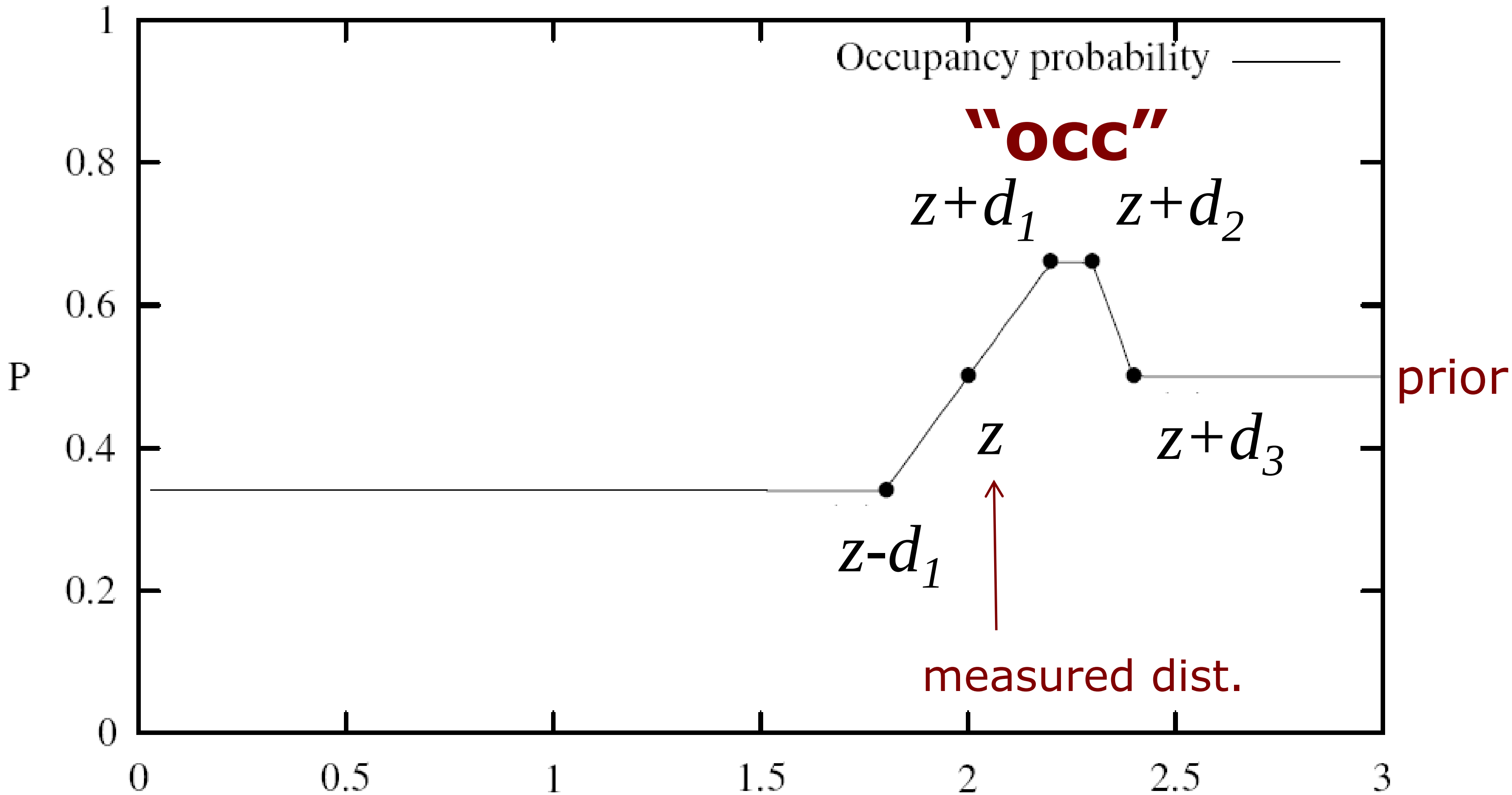
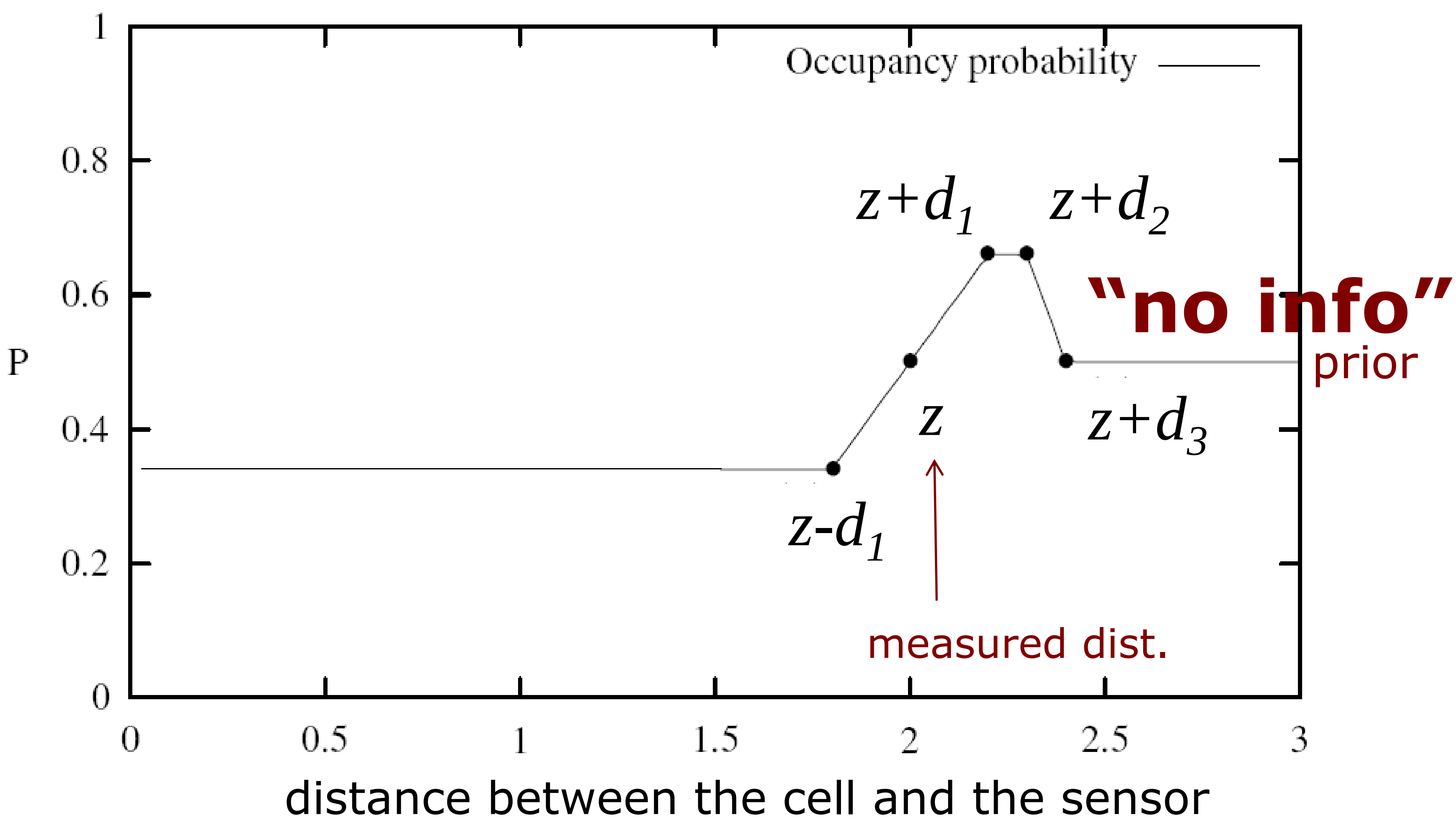


Occupancy Value Depending on the Measured Distance

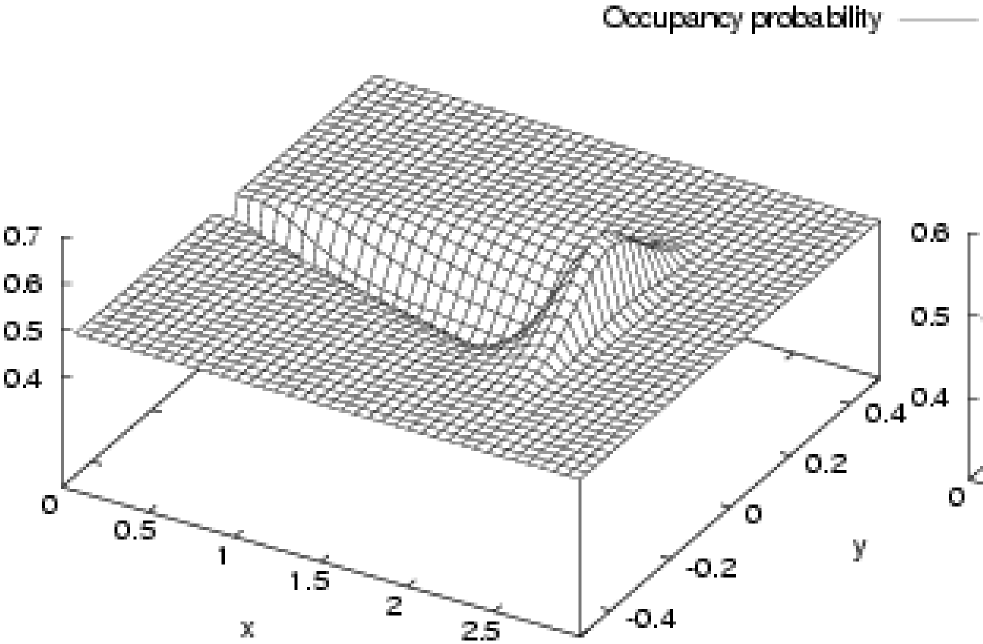


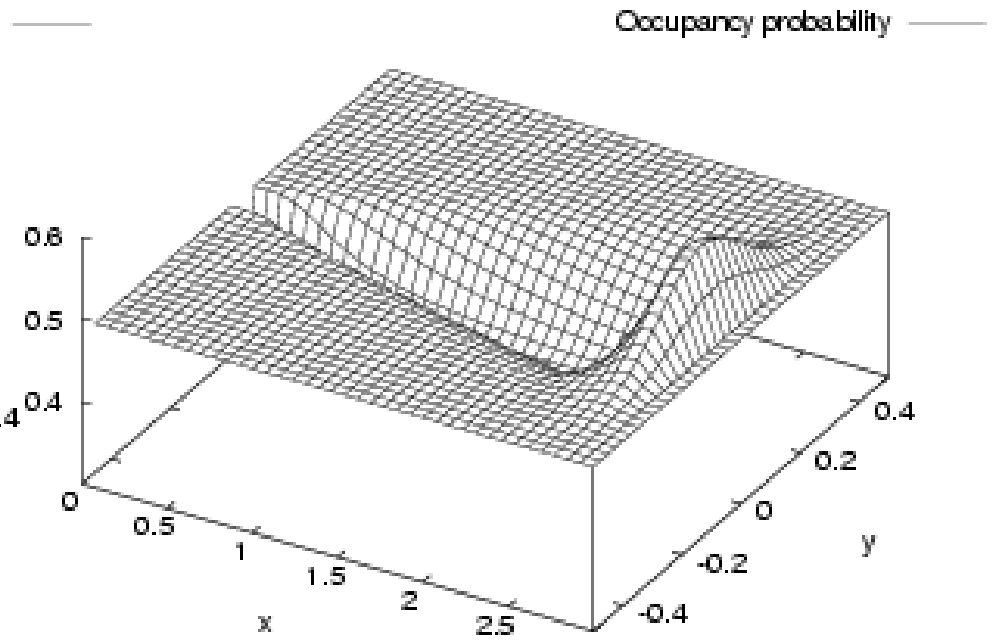
distance between the cell and the sensor

Occupancy Value Depending on the Measured Distance

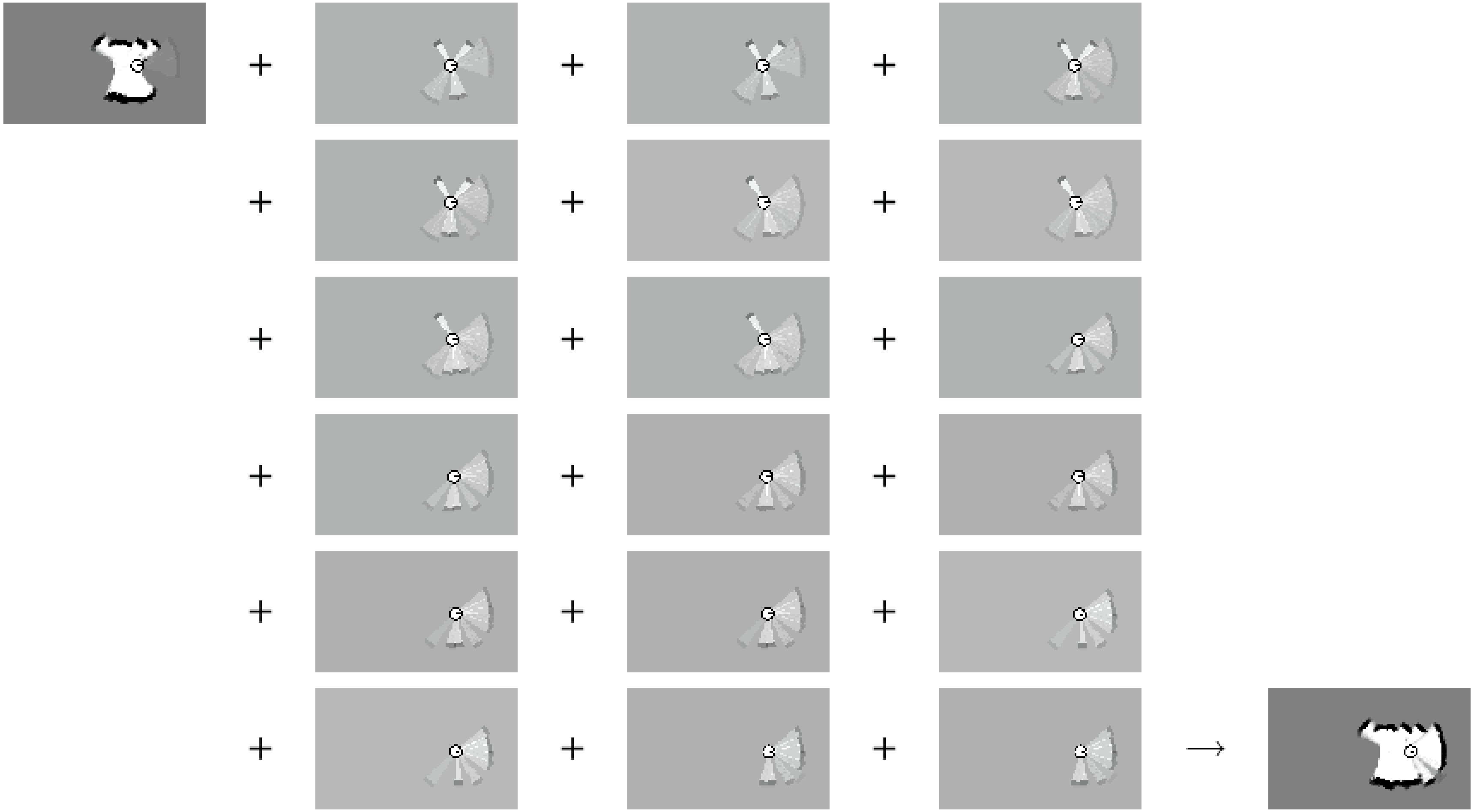


The Model in More Details

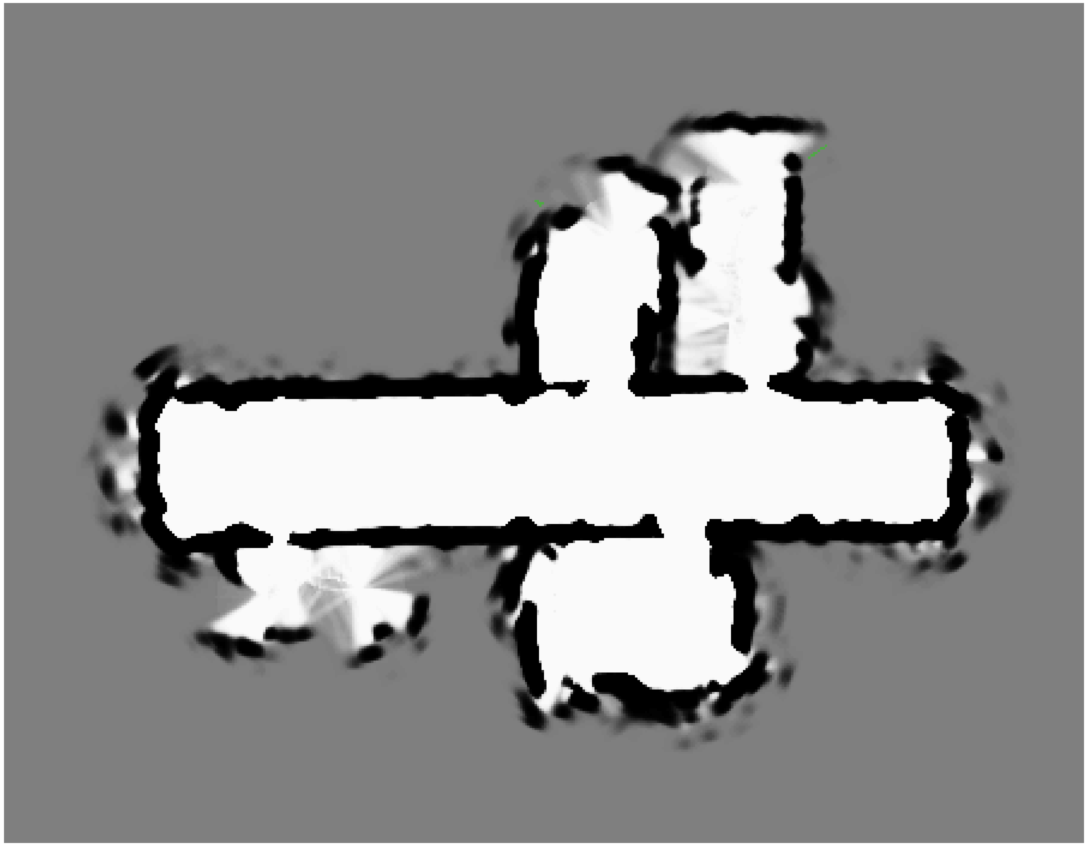




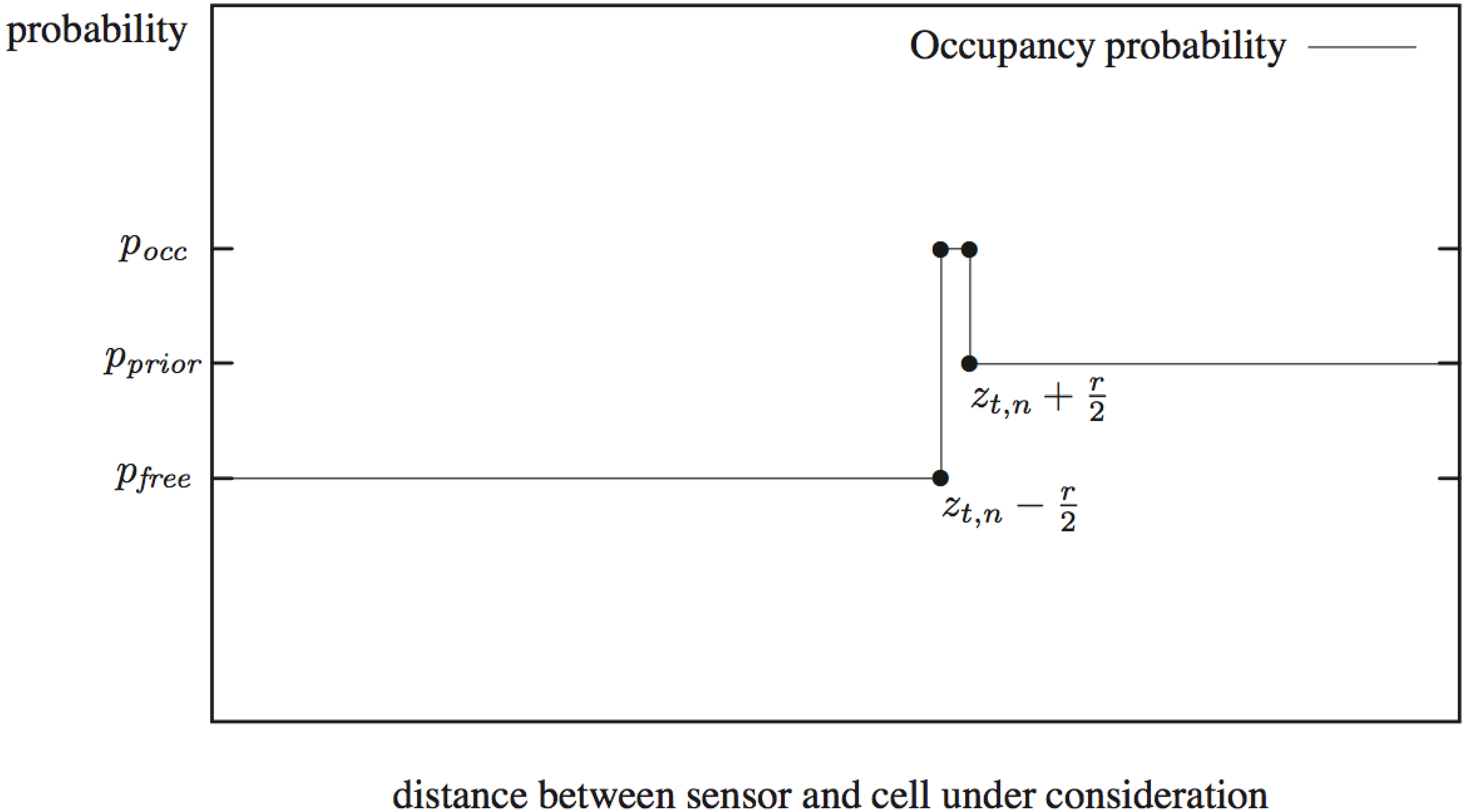
Example: Incremental Updating of Occupancy Grids



Resulting Map Obtained with 24 Sonar Range Sensors



Inverse Sensor Model for Laser Range Finders



Occupancy Grid Mapping

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- Developed for noisy sonar sensors
- Also called “mapping with know poses”

Occupancy Grid Mapping

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- Developed for noisy sonar sensors
- Also called "mapping with know poses"

- Lasers are coherent and precise
- Approximate the beam as a "line"

Maximum Likelihood Grid Maps

- Compute values for m that maximize

$$
\begin{aligned}
m^\star &= \operatorname{argmax}_m P(z_1, \cdots, z_t \mid m, x_1, \cdots, x_t) \\
&= \operatorname{argmax}_m \prod_{t=1}^{T} P(z_t \mid m, x_t) \\
&= \operatorname{argmax}_m \sum_{t=1}^{T} \ln P(z_t \mid m, x_t)
\end{aligned}
$$

since z_t independent and only depend on x_t

- The individual likelihood are Bernoulli

$$
p(z_{t,n} | x_t, m) = \begin{cases} \prod_{k=0}^{z_{t,n}-1} (1 - m_{f(x_t,n,k)}) & \text{if } \zeta_{t,n} = 1 \\ m_{f(x_t,n,z_{t,n})} \prod_{k=0}^{z_{t,n}-1} (1 - m_{f(x_t,n,k)}) & \zeta_{t,n} = 0 \end{cases}
$$

Maximum Likelihood Grid Maps

- Collecting the terms for each cell:

$$\mathrm{m}^\star = \operatorname{argmax}_m \sum_{j=1}^{J} \Big(\alpha_j \ln m_j + \beta_j \ln(1 - m_j) \Big)$$

- where we have

$$\alpha_j = \sum_{t=1}^{T} \sum_{n=1}^{N} I(f(x_t, n, z_{t,n}) = j) \cdot (1 - \zeta_{t,n})$$

$$\beta_j = \sum_{t=1}^{T} \sum_{n=1}^{N} \sum_{k=0}^{z_{t,n}-1} I(f(x_t, n, k) = j)$$

Maximum Likelihood Grid Maps

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$$\mathrm{m}^\star = \operatorname{argmax}_m \sum_{j=1}^{J} \left(\alpha_j \ln m_j + \beta_j \ln(1 - m_j) \right)$$

- where we have

$$\alpha_j = \sum_{t=1}^{T} \sum_{n=1}^{N} I(f(x_t, n, z_{t,n}) = j) \cdot (1 - \zeta_{t,n}) \qquad \boxed{hits(j)}$$

$$\beta_j = \sum_{t=1}^{T} \sum_{n=1}^{N} \sum_{k=0}^{z_{t,n}-1} I(f(x_t, n, k) = j) \qquad \boxed{misses(j)}$$

- Setting the gradient to zero we obtain

$$\frac{\partial}{\partial m_j} = \frac{\alpha_j}{m_j} - \frac{\beta_j}{1-m_j} = 0 \qquad m_j = \frac{\alpha_j}{\alpha_j + \beta_j}$$

Posterior Distribution of Cells

- Maximum likelihood neglects the prior
- We would like to compute

$$P(m \,| x_1, \cdots, x_t, z_1, \cdots, z_t) =$$
$$= \eta P(z_1, \cdots, z_t \mid m, x_1, \cdots, x_t) P(m)$$

- Likelihood is still Bernoulli
- Conjugate prior: Beta distribution

$$p(m_j; \bar{\alpha}, \bar{\beta}) = \frac{1}{\mathrm{B}(\bar{\alpha}, \bar{\beta})} m_j^{\bar{\alpha}-1} (1 - m_j)^{\bar{\beta}-1}$$

Posterior Distribution of Cells

- How does the posterior look like?
- Conjugate prior: Beta distribution

$$p(m_j; \bar{\alpha}, \bar{\beta}) = \frac{1}{\mathrm{B}(\bar{\alpha}, \bar{\beta})} m_j^{\bar{\alpha}-1} (1 - m_j)^{\bar{\beta}-1}$$

- Likelihood Bernoulli

$$P(z_1, \cdots, z_t \mid m_j, x_1, \cdots, x_t) = m_j^{\alpha_j} (1 - m_j)^{\beta_j}$$

- Posterior

$$p(m_j; \hat{\alpha}, \hat{\beta}) = \boxed{\quad ? \quad}$$

Posterior Distribution of Cells

- How does the posterior look like?
- Conjugate prior: Beta distribution

$$p(m_j; \bar{\alpha}, \bar{\beta}) = \frac{1}{\mathrm{B}(\bar{\alpha}, \bar{\beta})} m_j^{\bar{\alpha}-1} (1 - m_j)^{\bar{\beta}-1}$$

- Likelihood Bernoulli

$$P(z_1, \cdots, z_t \mid m_j, x_1, \cdots, x_t) = m_j^{\alpha_j} (1 - m_j)^{\beta_j}$$

- Posterior

$$p(m_j; \hat{\alpha}, \hat{\beta}) = \frac{1}{\mathrm{B}(\bar{\alpha} + \alpha_j, \bar{\beta} + \beta_j)} m_j^{\bar{\alpha}+\alpha_j-1} (1 - m_j)^{\bar{\beta}+\beta_j-1}$$

Posterior Estimates of Cells

- Maximum a posteriori (mode of Beta)

$$m^\star = \text{argmax}_m P(m \mid x_1, \cdots, x_t, z_1, \cdots, z_t) = \frac{\hat{\alpha} - 1}{\hat{\alpha} + \hat{\beta} - 2}$$

- Expected value (unbiased)

$$m^\star = \mathbb{E}[P(m \mid x_1, \cdots, x_t, z_1, \cdots, z_t)] = \frac{\hat{\alpha}}{\hat{\alpha} + \hat{\beta}}$$

- Maximum likelihood (revised)
  - Maximum a posteriori with uniform prior
  - Uniform prior for Beta $\bar{\alpha} = 1$ $\bar{\beta} = 1$

$$m^\star = \boxed{\textbf{?}}$$

Posterior Estimates of Cells

- Maximum a posteriori (mode of Beta)

$$m^\star = \mathrm{argmax}_m P(m \mid x_1, \cdots, x_t, z_1, \cdots, z_t) = \frac{\hat{\alpha} - 1}{\hat{\alpha} + \hat{\beta} - 2}$$

- Expected value (unbiased)

$$m^\star = \mathbb{E}[P(m \mid x_1, \cdots, x_t, z_1, \cdots, z_t)] = \frac{\hat{\alpha}}{\hat{\alpha} + \hat{\beta}}$$

- Maximum likelihood (revised)
  - Maximum a posteriori with uniform prior
  - Uniform prior for Beta $\bar{\alpha} = 1$ $\bar{\beta} = 1$

$$m^\star = \frac{\hat{\alpha} - 1}{\hat{\alpha} + \hat{\beta} - 2} = \boxed{\quad ? \quad}$$

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$$m^\star = \frac{\hat{\alpha} - 1}{\hat{\alpha} + \hat{\beta} - 2} = \frac{\bar{\alpha} + \alpha_j - 1}{\bar{\alpha} + \alpha_j + \bar{\beta} + \beta_j - 2} = \boxed{?}$$

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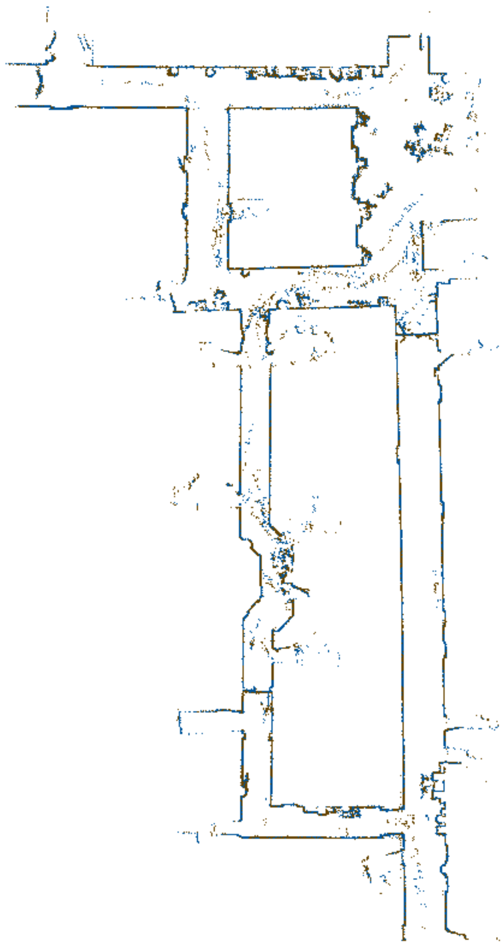
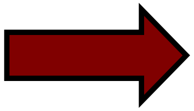
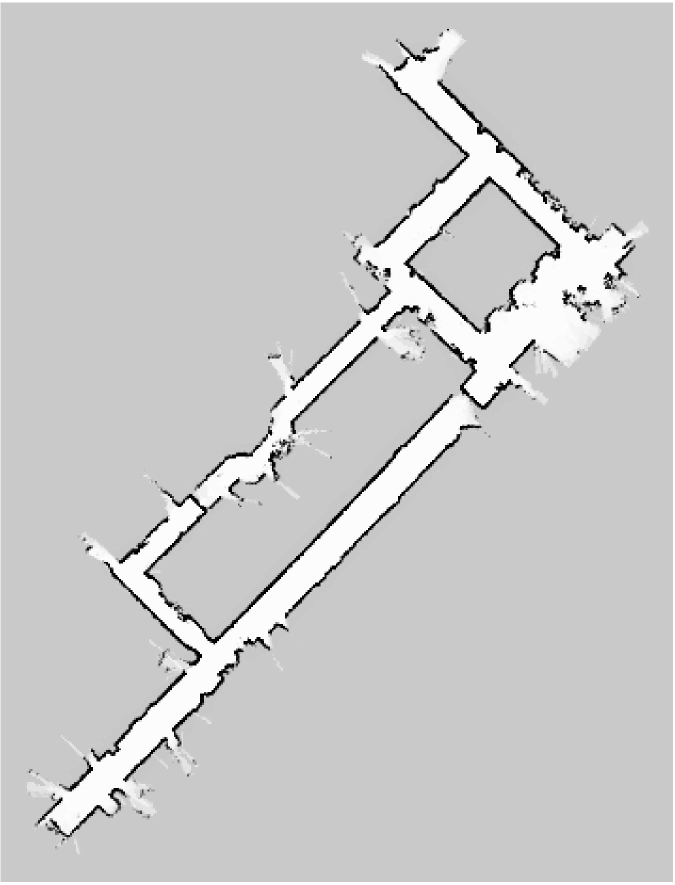
Occupancy Grids
From Laser Scans to Maps

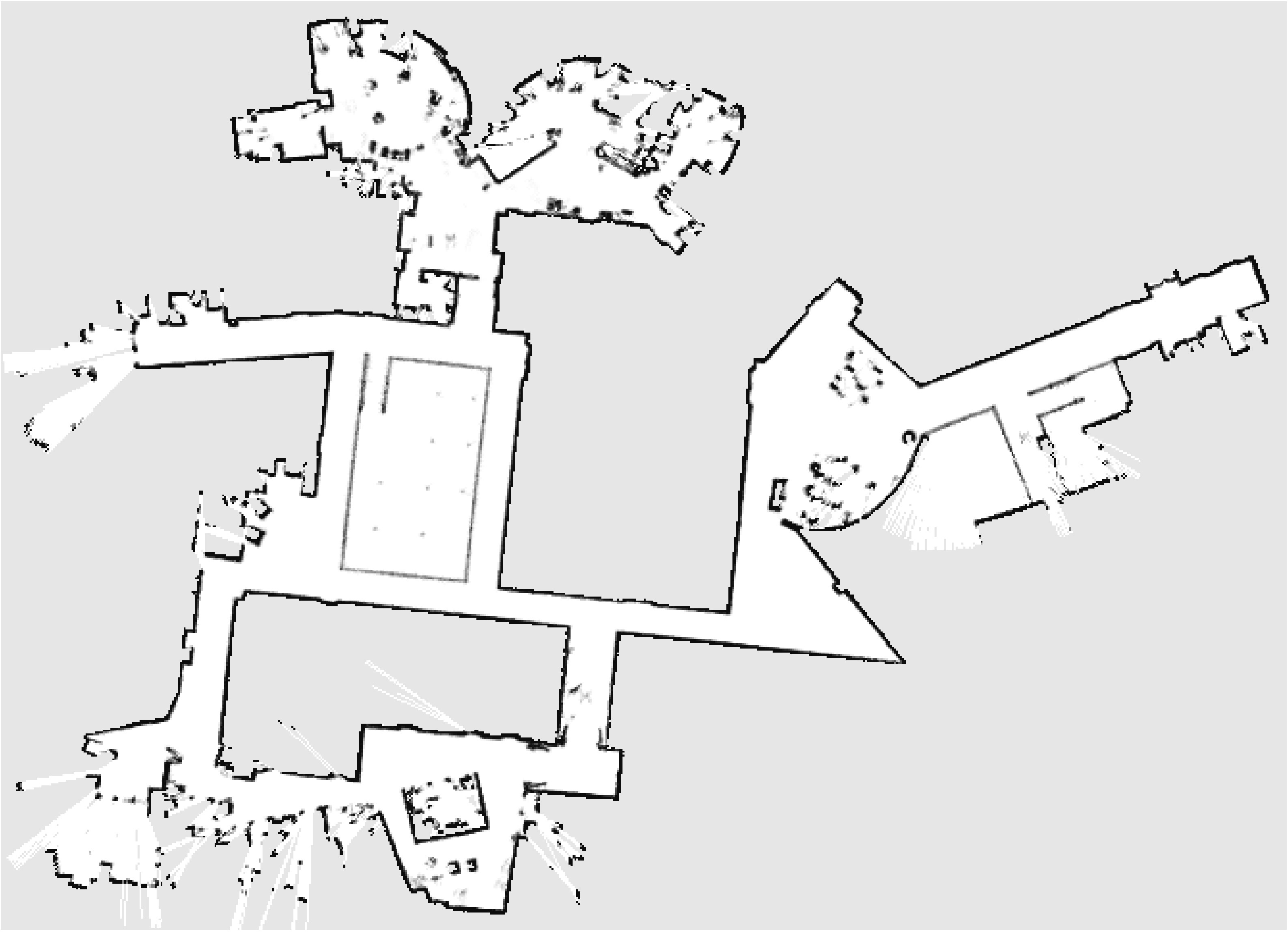




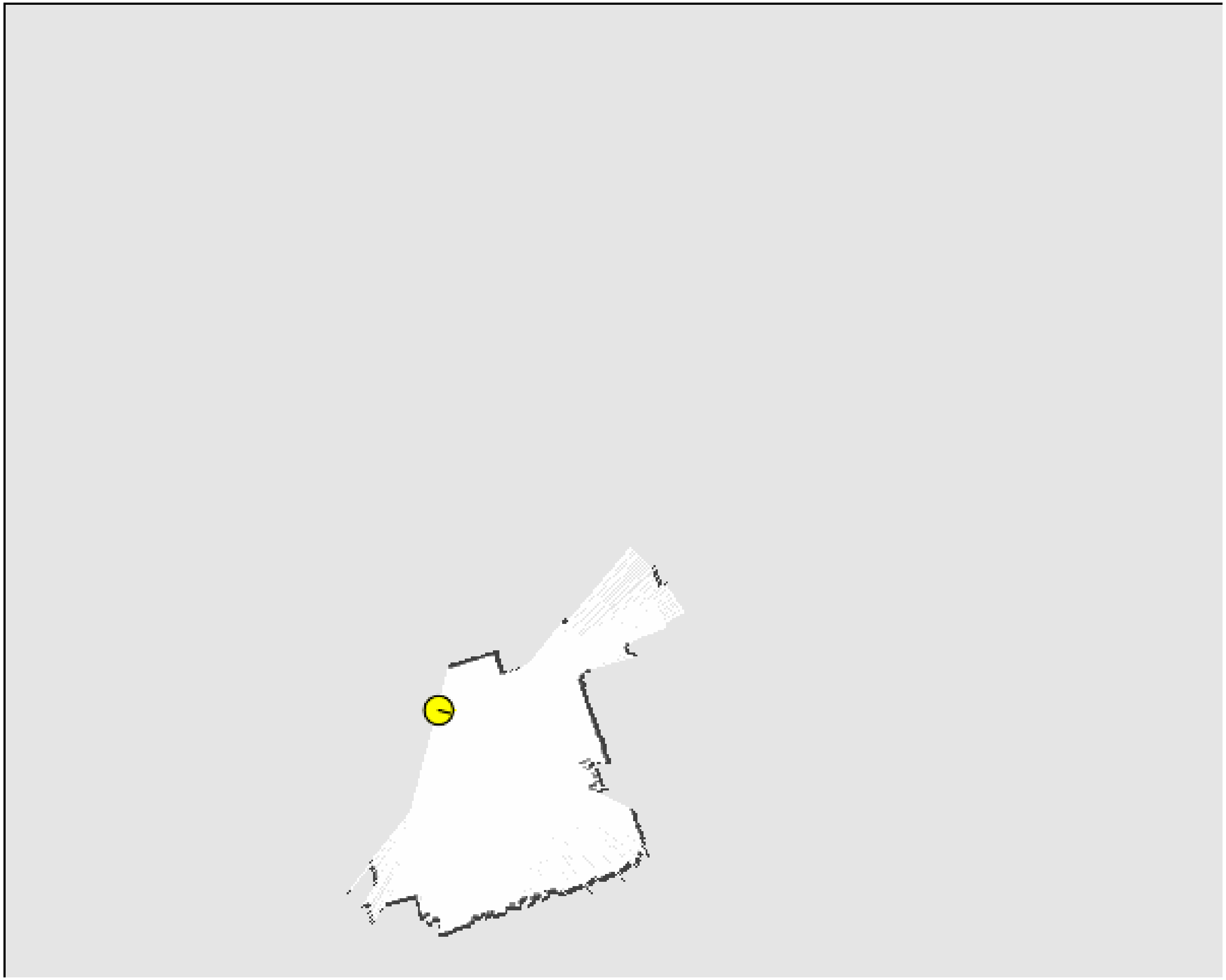


Courtesy: D. Hähnel

Example: MIT CSAIL 3rd Floor



Uni Freiburg Building 106



Occupancy Grid Map Summary

- Occupancy grid maps discretize the space into independent cells
- Each cell is a binary random variable estimating if the cell is occupied
- Static state binary Bayes filter per cell
- Mapping with known poses is easy
- Log odds model is fast to compute
- No need for predefined features

Literature

Static state binary Bayes filter

- Thrun et al.: “Probabilistic Robotics”, Chapter 4.2

Occupancy Grid Mapping

- Thrun et al.: “Probabilistic Robotics”, Chapter 9.1+9.2

Slide Information

- These slides have been created by Cyrill Stachniss as part of the robot mapping course taught in 2012/13 and 2013/14. I created this set of slides partially extending existing material of Edwin Olson, Pratik Agarwal, and myself.
- I tried to acknowledge all people that contributed image or video material. In case I missed something, please let me know. If you adapt this course material, please make sure you keep the acknowledgements.
- Feel free to use and change the slides. If you use them, I would appreciate an acknowledgement as well. To satisfy my own curiosity, I appreciate a short email notice in case you use the material in your course.
- My video recordings are available through YouTube:
  http://www.youtube.com/playlist?list=PLgnQpQtFTOGQrZ4O5QzbIHgl3b1JHimN_&feature=g-list

Cyrill Stachniss, 2014
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