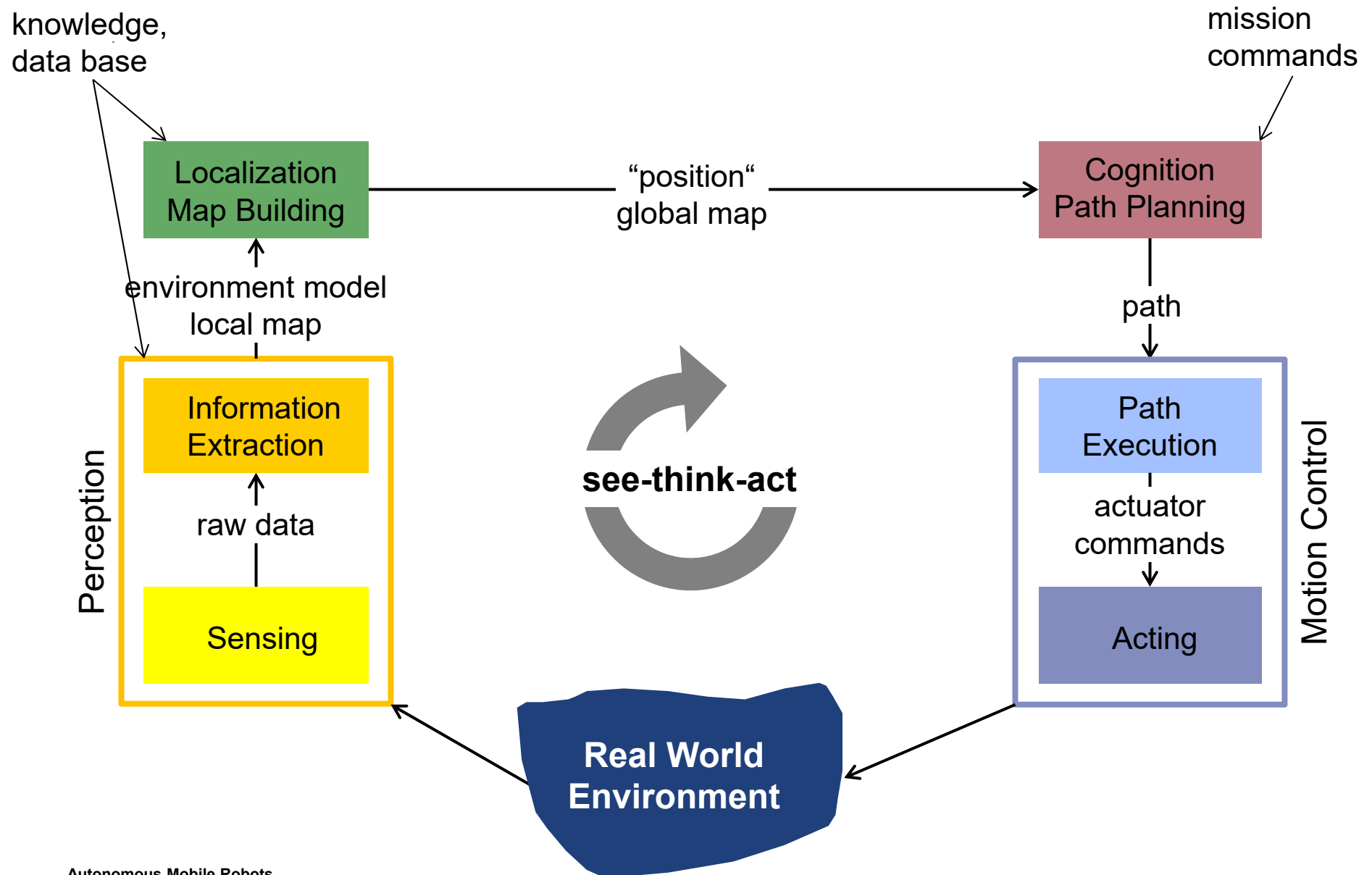


Spring 2018



Localization II

Roland Siegwart, Margarita Chli, Juan Nieto, Nick Lawrance

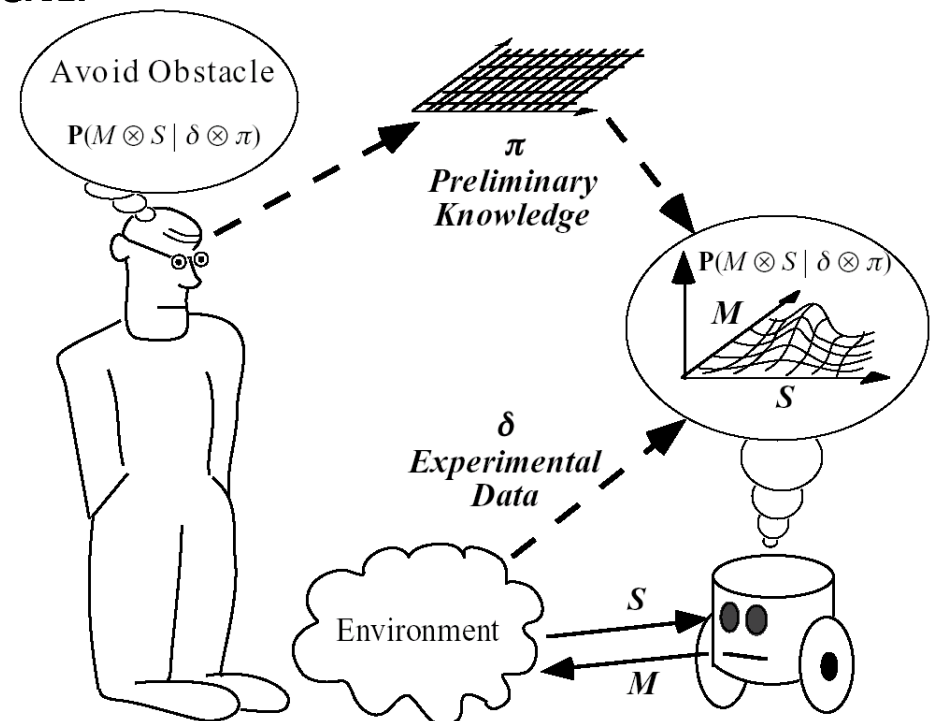


Probabilistic Reasoning (e.g. Bayesian)

- Reasoning in the presence of uncertainties and incomplete information
- Combining preliminary information and models with learning from experimental data

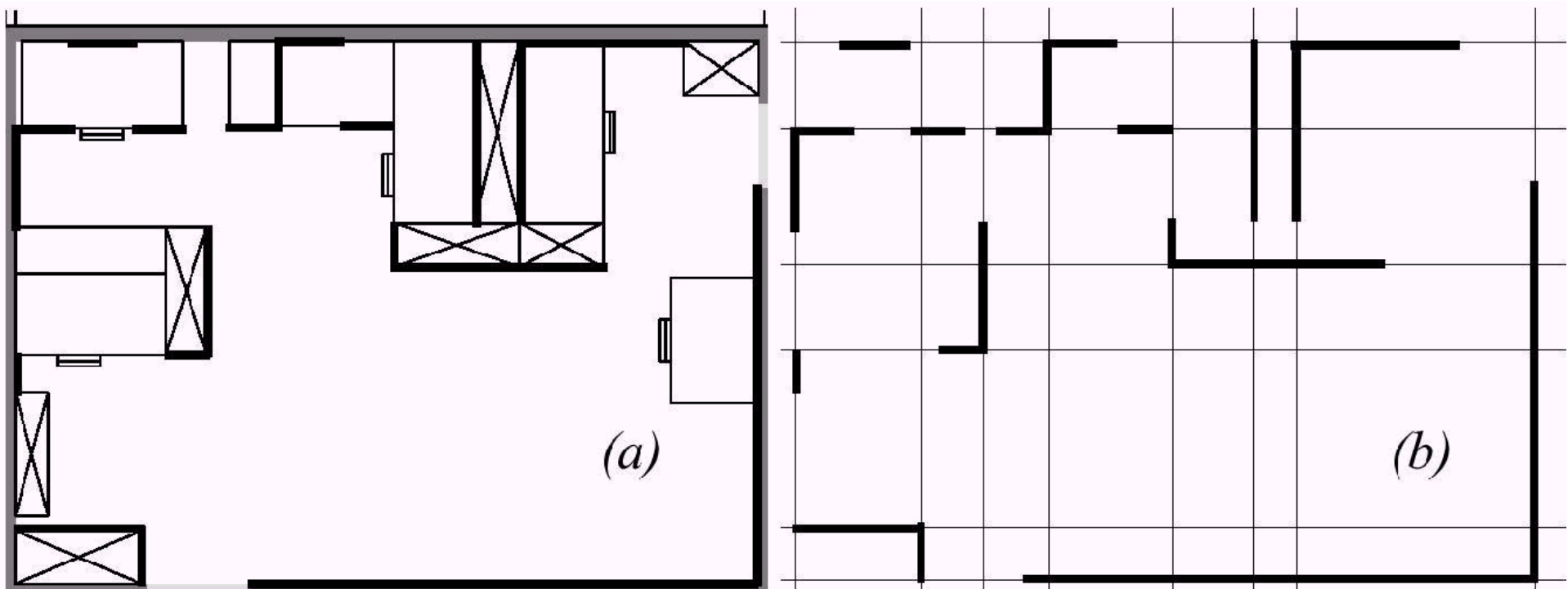
$$p(x|y) = \frac{p(y|x)p(x)}{p(y)}$$

“optimization”



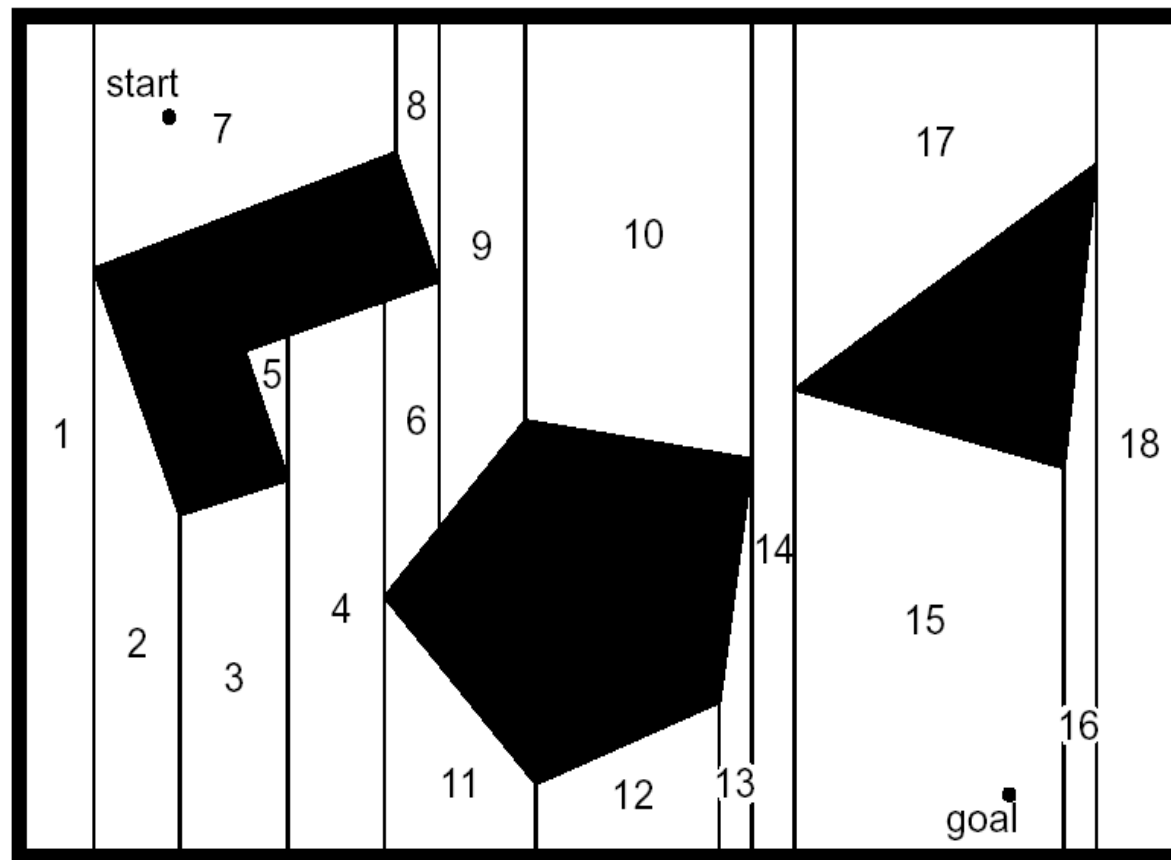
Map Representation | *Continuous Line-Based*

- a) Architecture map
- b) Representation with set of finite or infinite lines



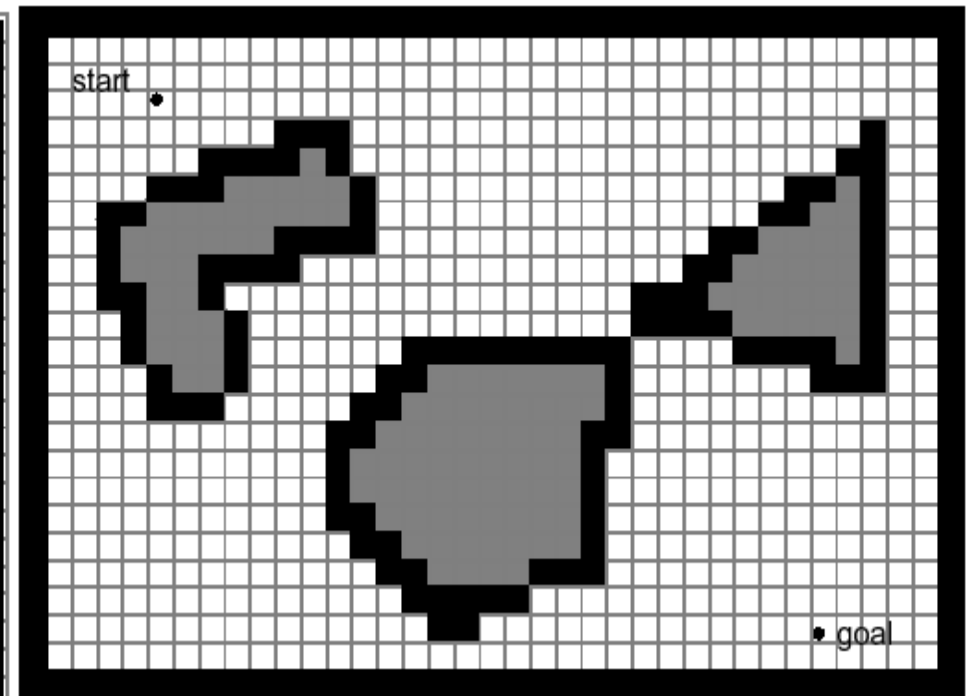
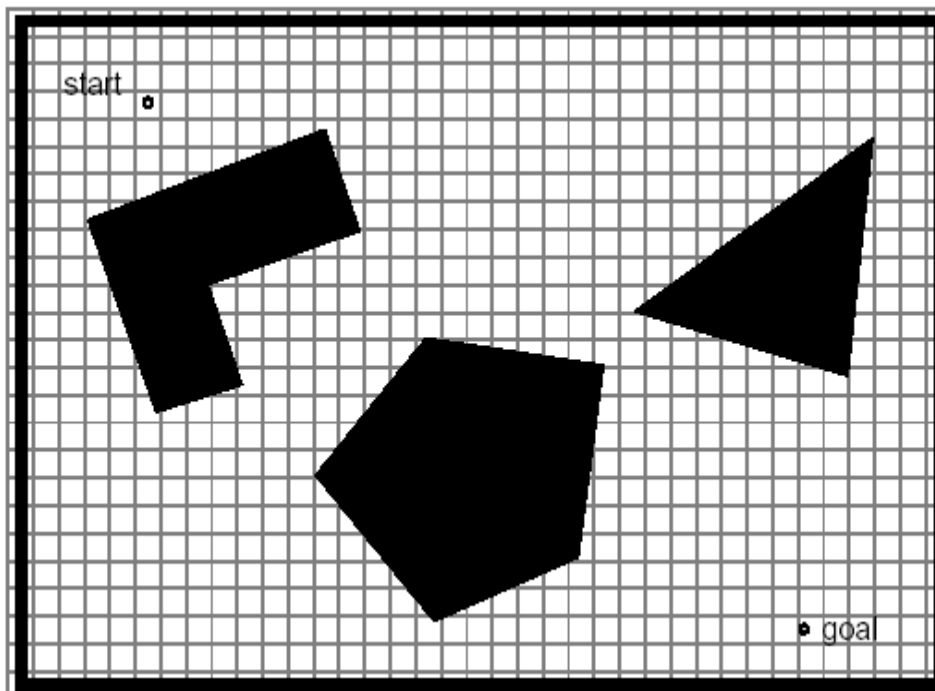
Map Representation | *Exact cell decomposition*

- Exact cell decomposition - Polygons



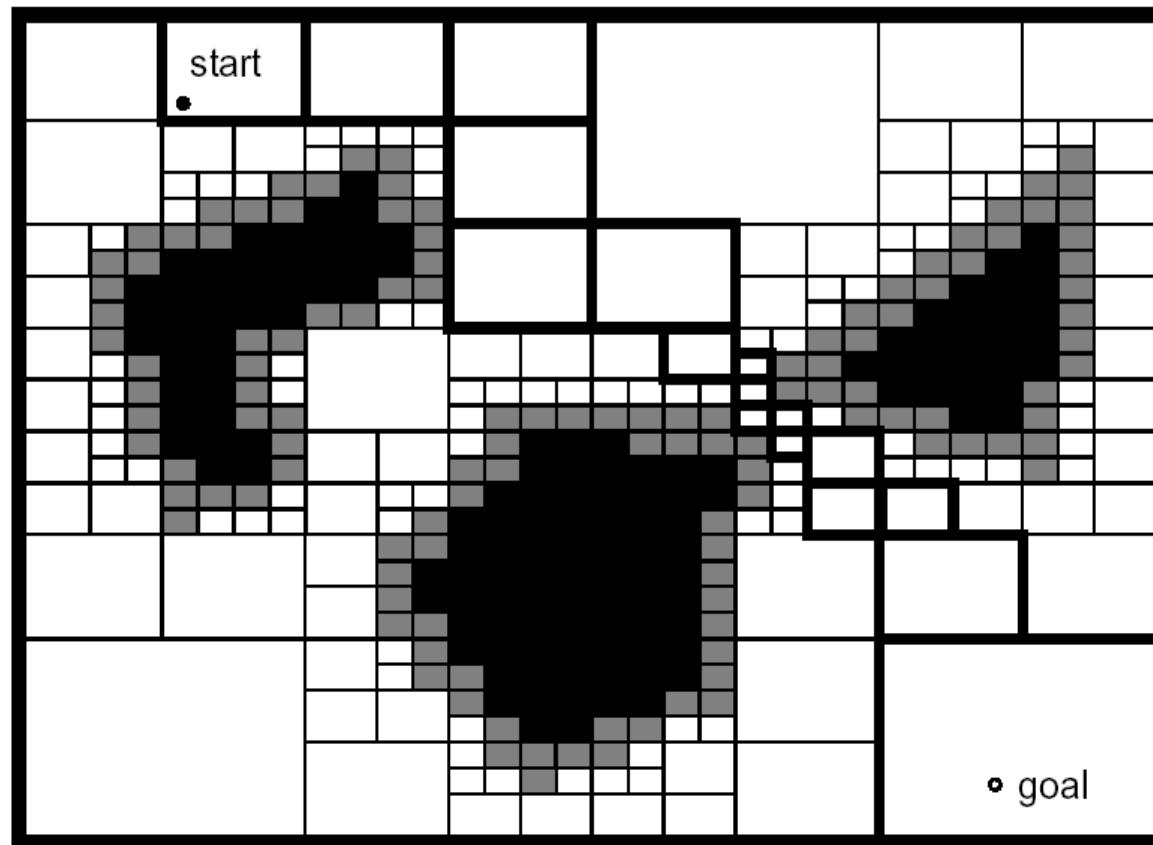
Map Representation | *Approximate cell decomposition*

- Fixed cell decomposition (occupancy grid)
 - Narrow passages disappear



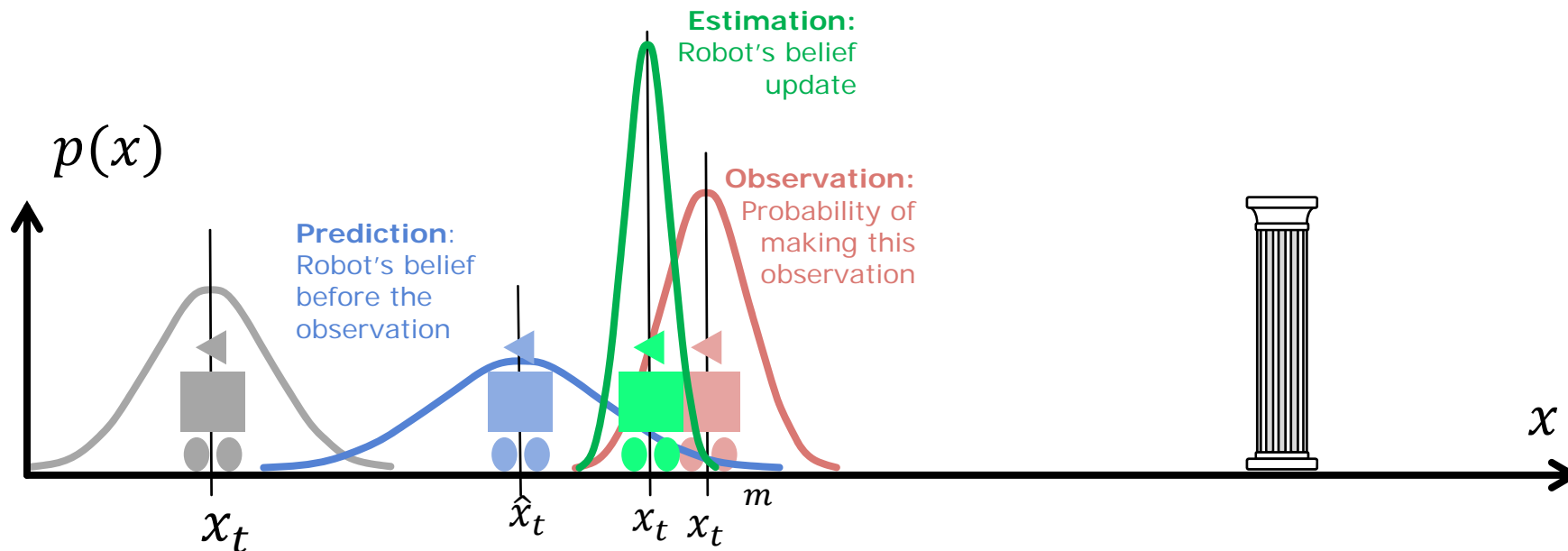
Map Representation | *Adaptive cell decomposition*

- Fixed cell decomposition
 - Narrow passages disappear



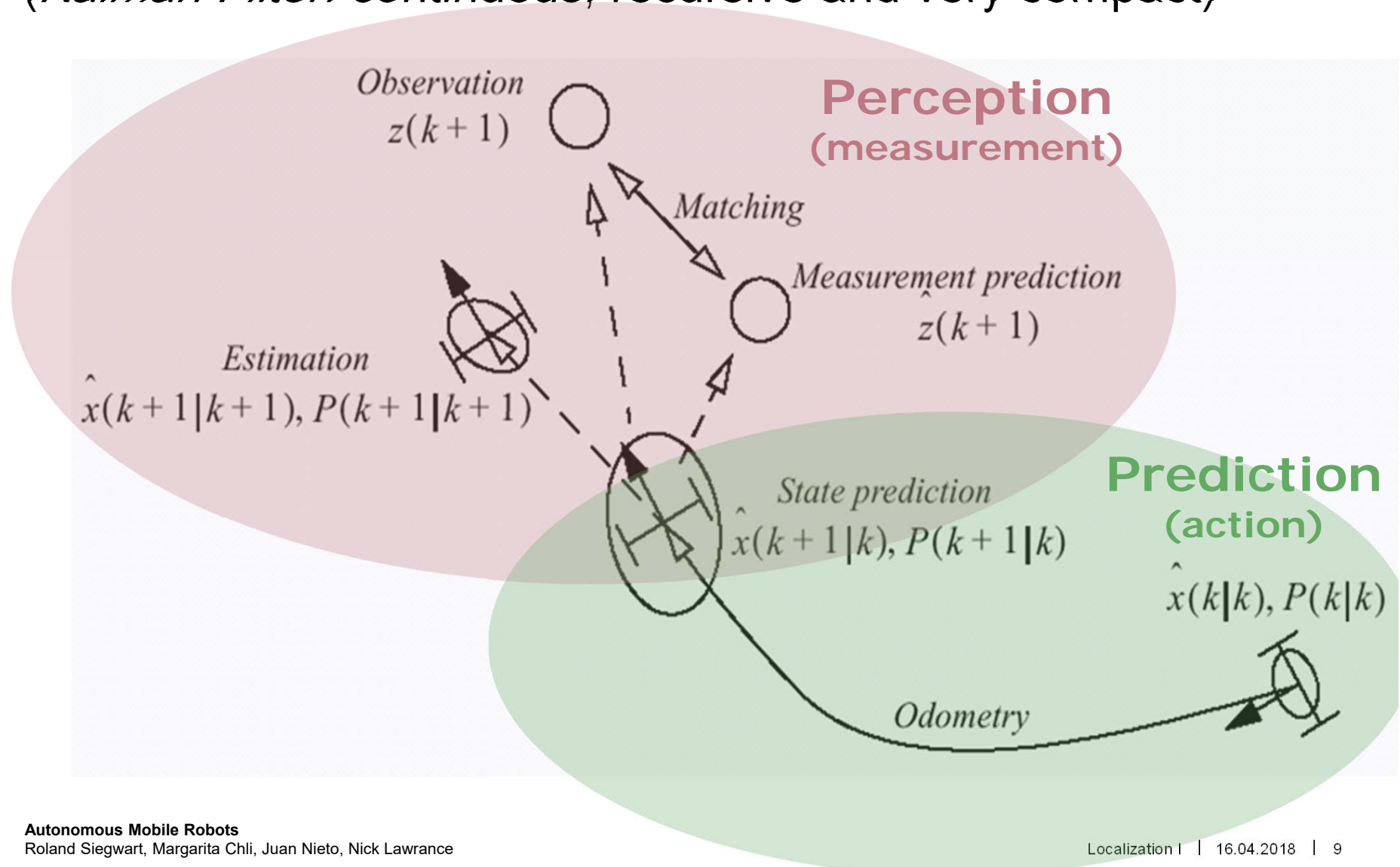
Kalman Filter Localization | in summery

1. **Prediction (ACT)** based on previous estimate and odometry
2. **Observation (SEE)** with on-board sensors
3. **Measurement prediction** based on prediction and map
4. **Matching** of observation and map
5. **Estimation** → position update (posteriori position)

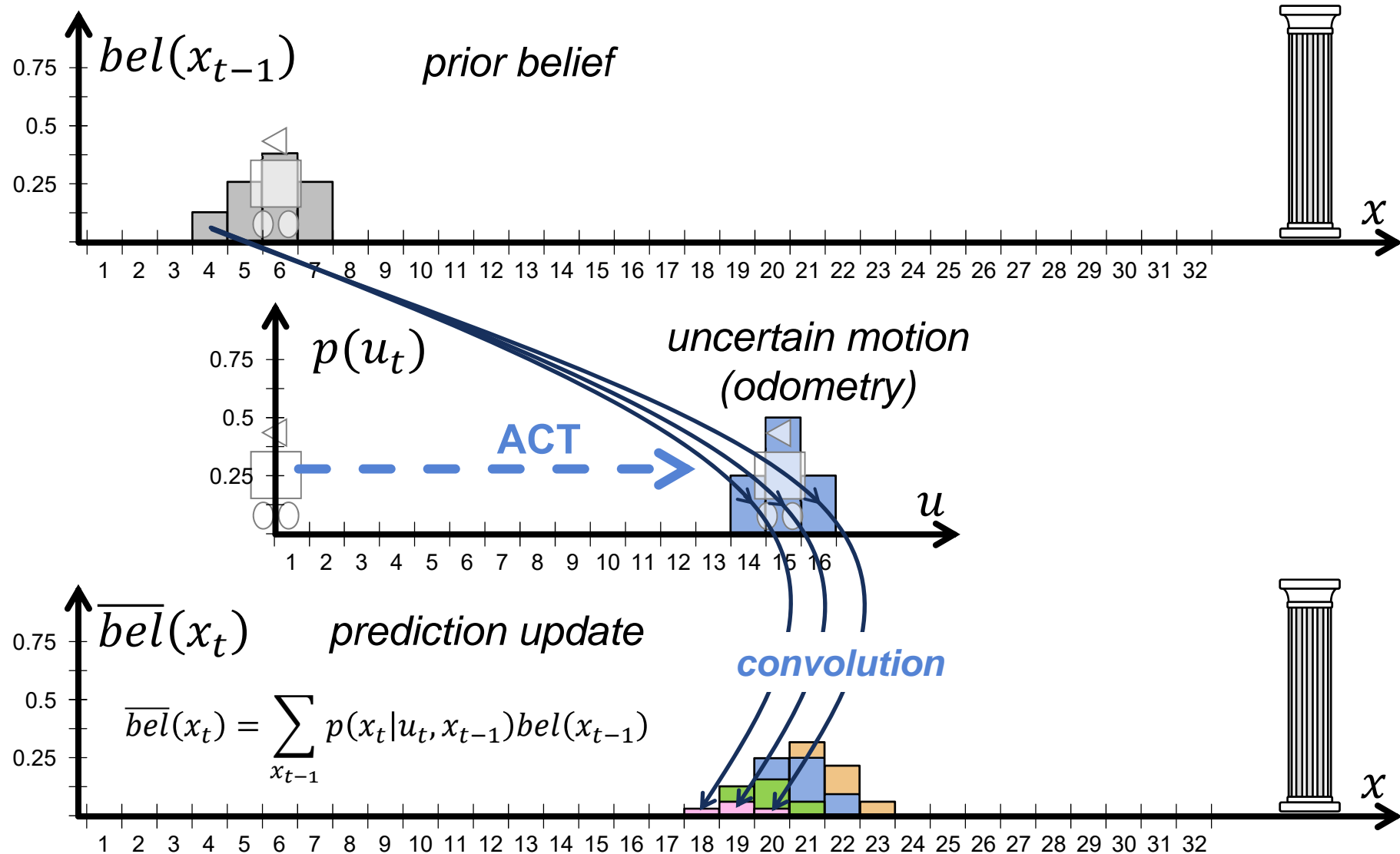


Localization: Probabilistic Position Estimation

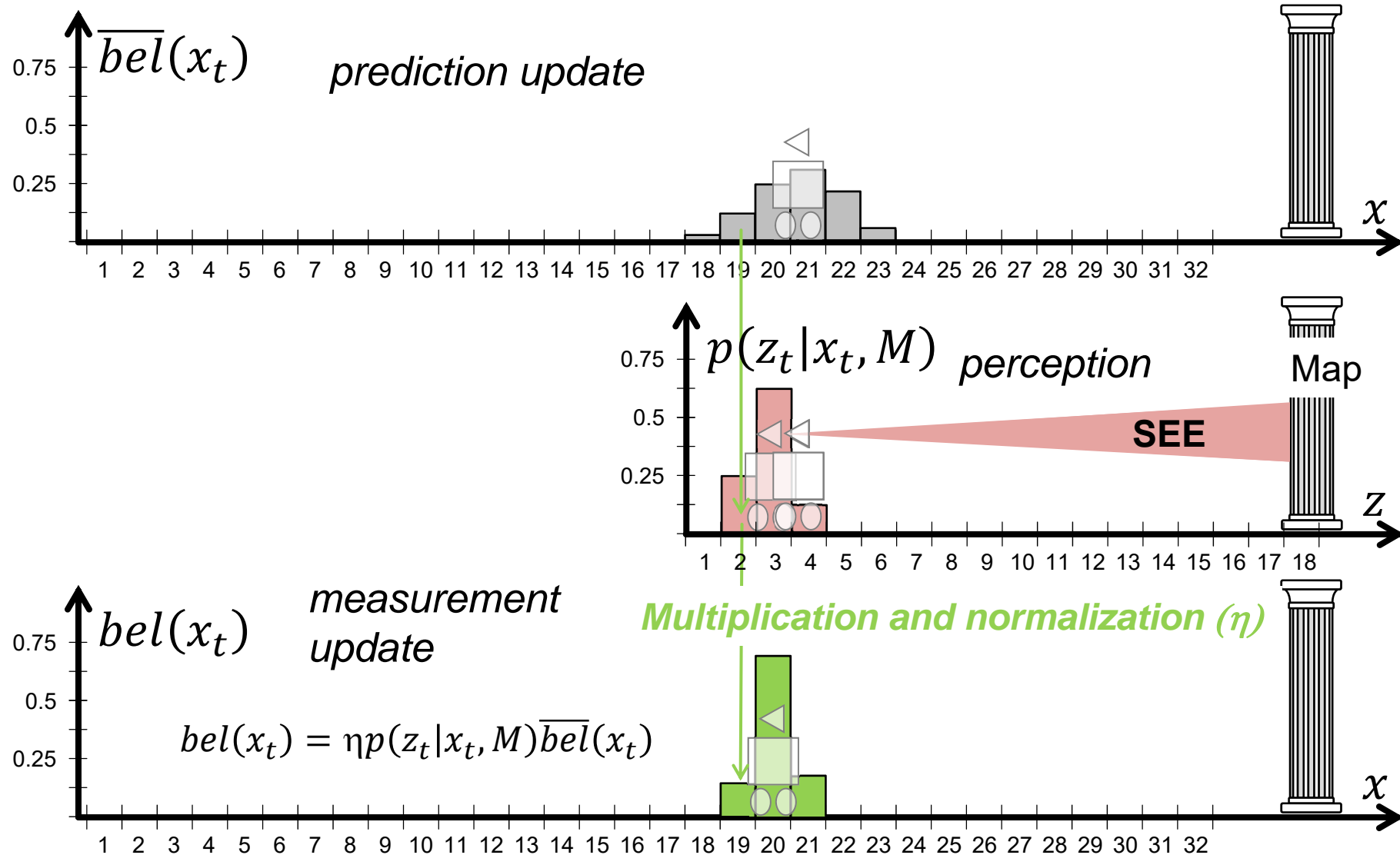
(Kalman Filter: continuous, recursive and very compact)



ACT | using motion model and its uncertainties



SEE | estimation of position based on perception and map

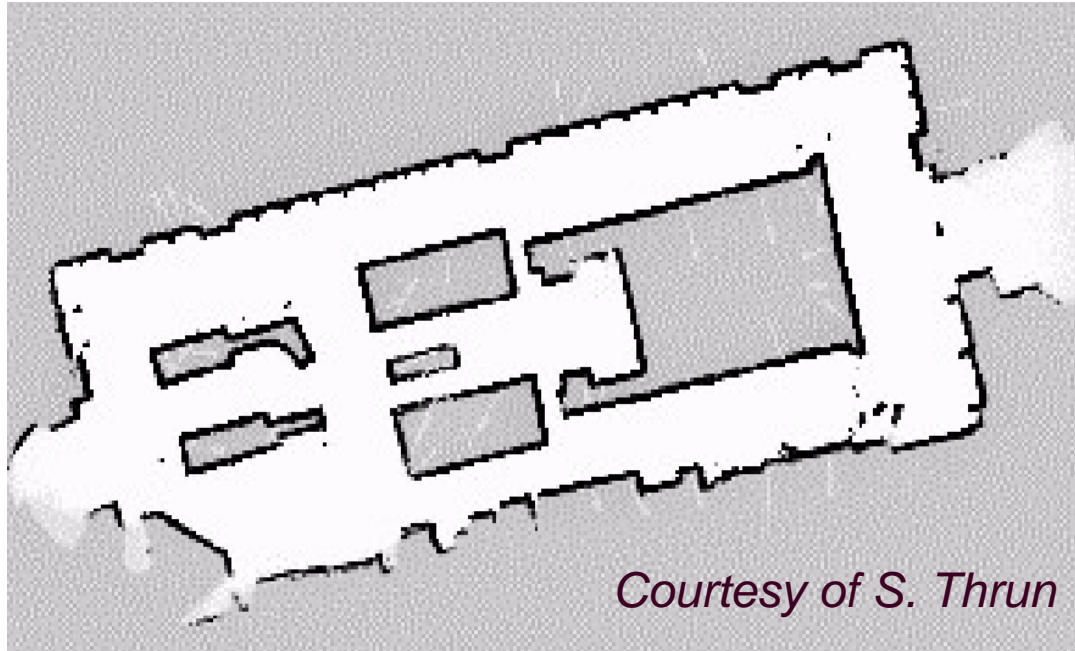


Kalman Filter Localization

Markov versus Kalman localization

Markov	Kalman
PROS <ul style="list-style-type: none">▪ localization starting from any unknown position▪ recovers from ambiguous situation	PROS <ul style="list-style-type: none">▪ Tracks the robot and is inherently very precise and efficient
CONS <ul style="list-style-type: none">▪ However, to update the probability of all positions within the whole state space at any time requires a discrete representation of the space (grid). The required memory and calculation power can thus become very important if a fine grid is used.	CONS <ul style="list-style-type: none">▪ If the uncertainty of the robot becomes too large (e.g. collision with an object) the Kalman filter will fail and the position is definitively lost

Map Representation | *Approximate cell decomposition*



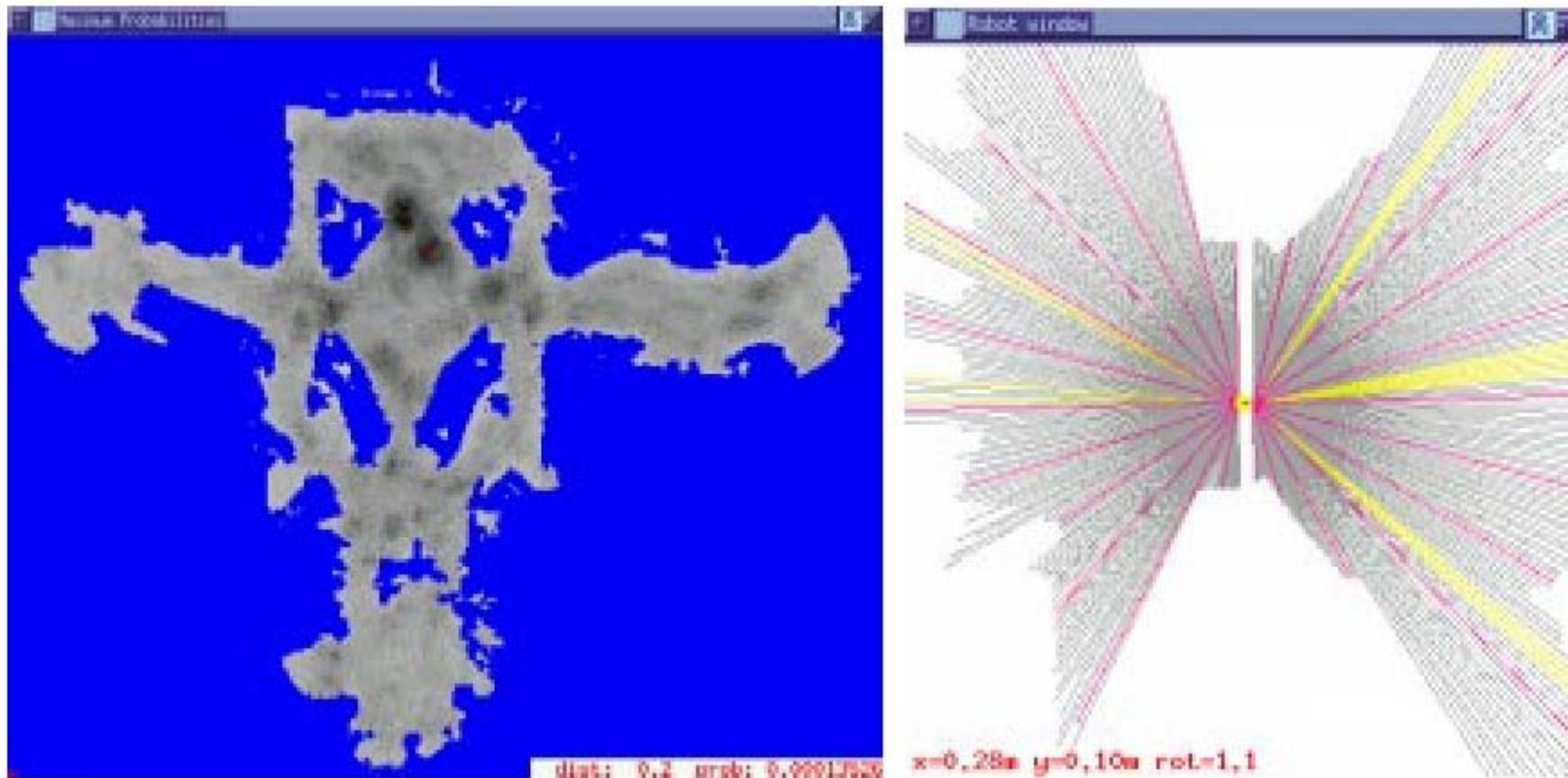
- Occupancy grid example
 - 0 indicates that the cell has not been hit by any ranging measurements (free space)
 - 1 indicates that the cell has been hit one or multiple times by ranging measurements (occupied space)
 - Can change over time (e.g. dynamic obstacles)

Markov Localization

Case Study – Grid Map

*Courtesy of
W. Burgard*

- Example 2: Museum
 - Laser scan 1

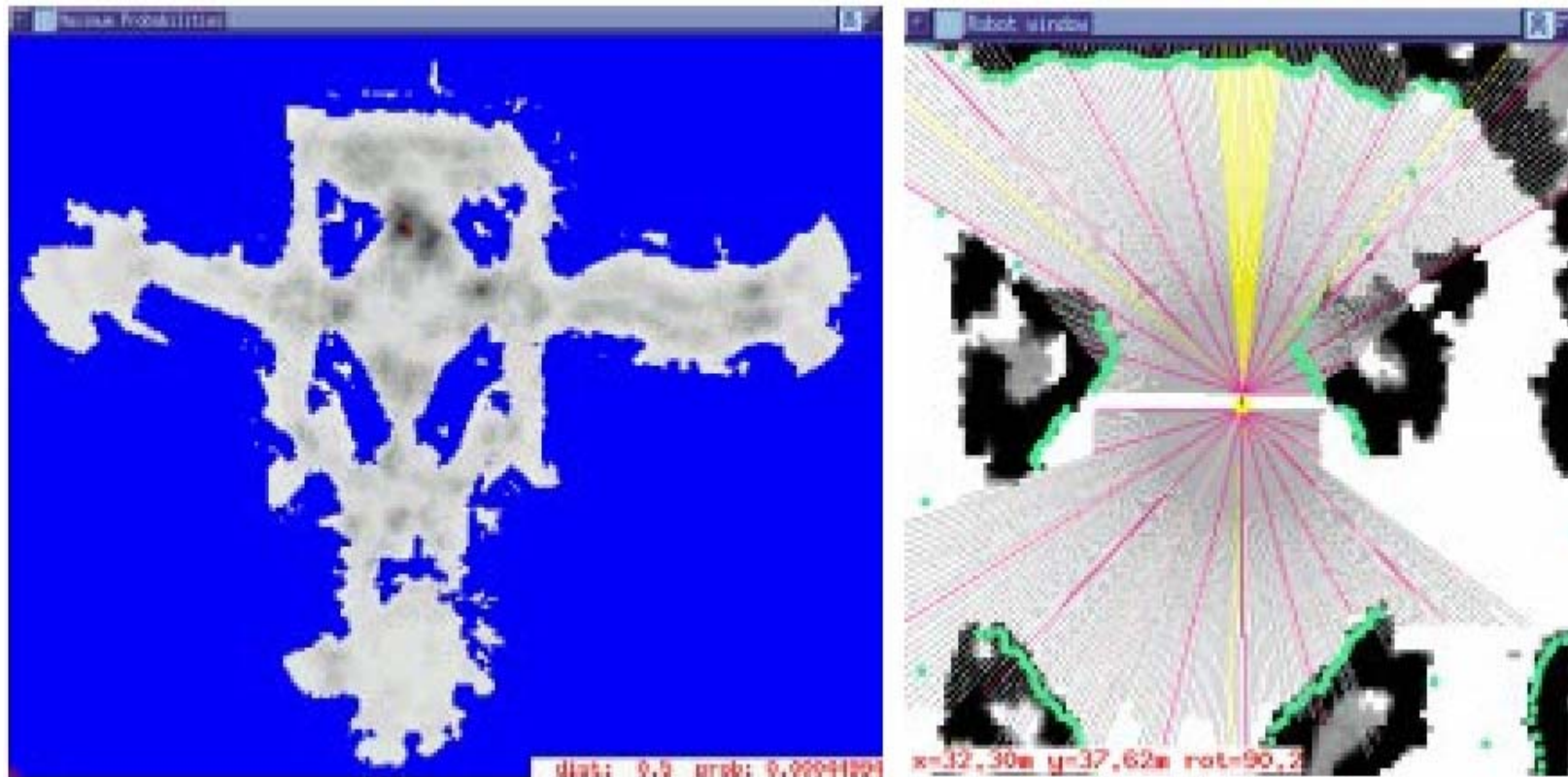


Markov Localization

Case Study – Grid Map

*Courtesy of
W. Burgard*

- Example 2: Museum
 - Laser scan 2

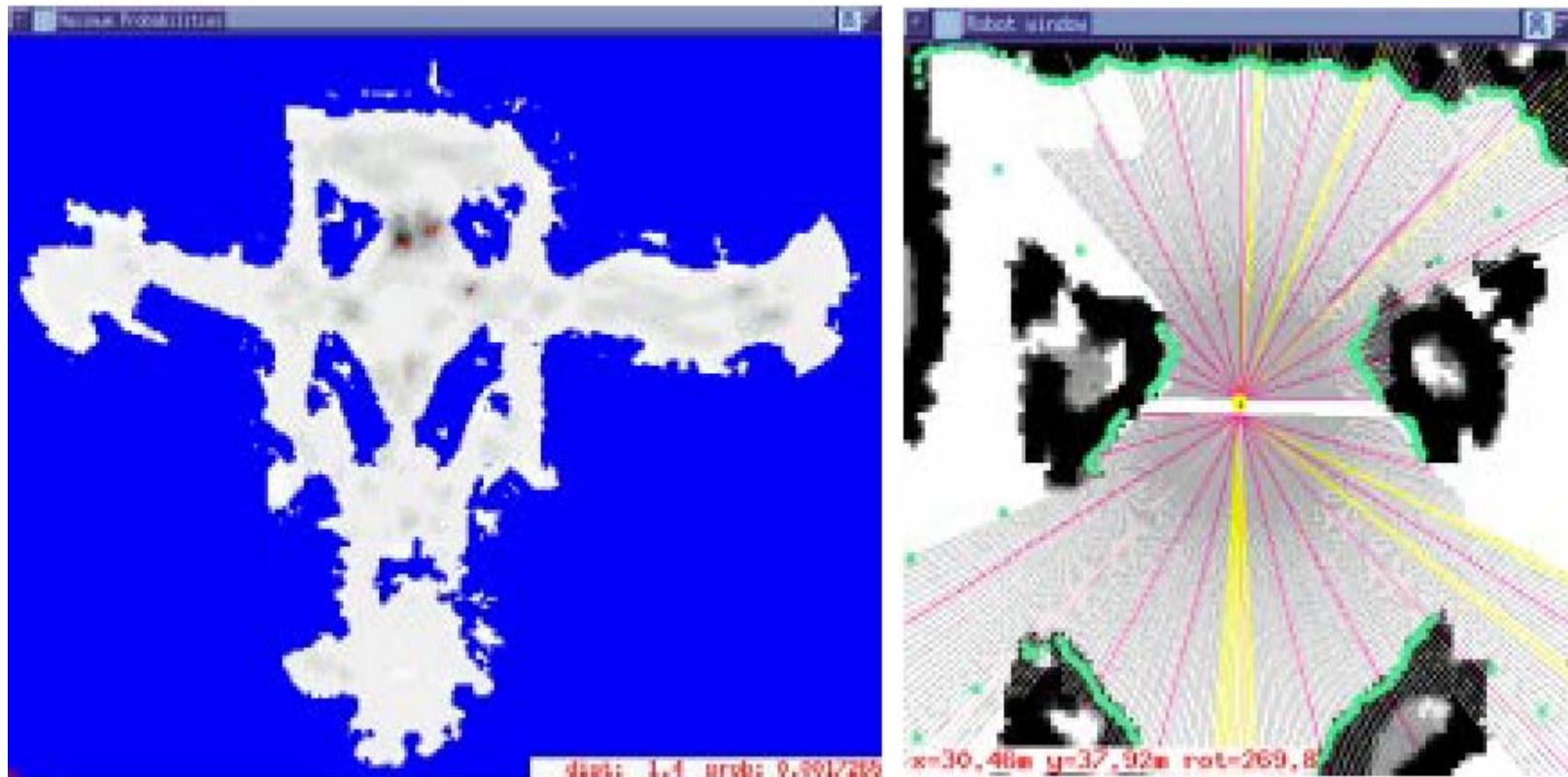


Markov Localization

Case Study – Grid Map

*Courtesy of
W. Burgard*

- Example 2: Museum
 - Laser scan 3

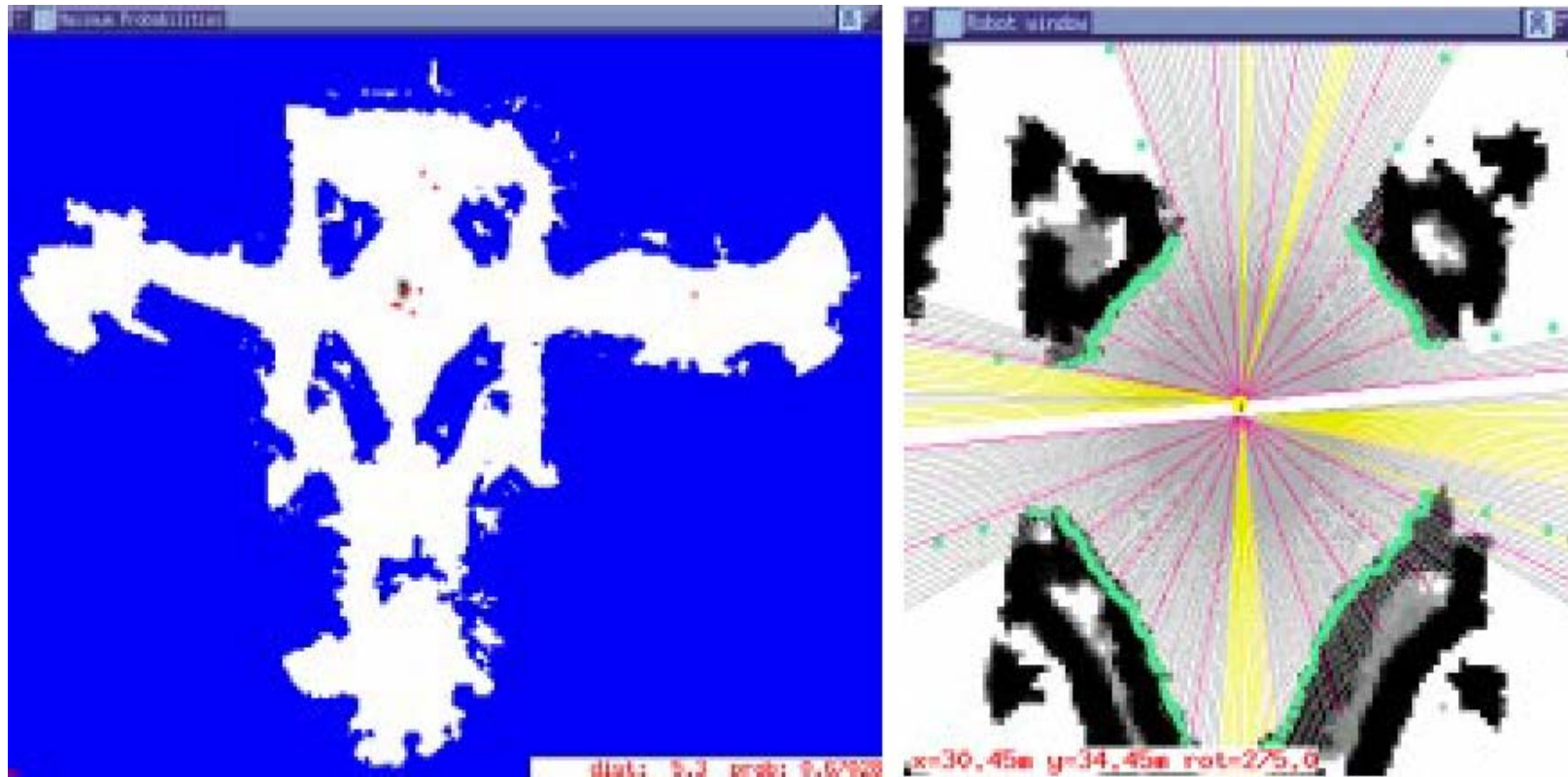


Markov Localization

Case Study – Grid Map

*Courtesy of
W. Burgard*

- Example 2: Museum
 - Laser scan 13

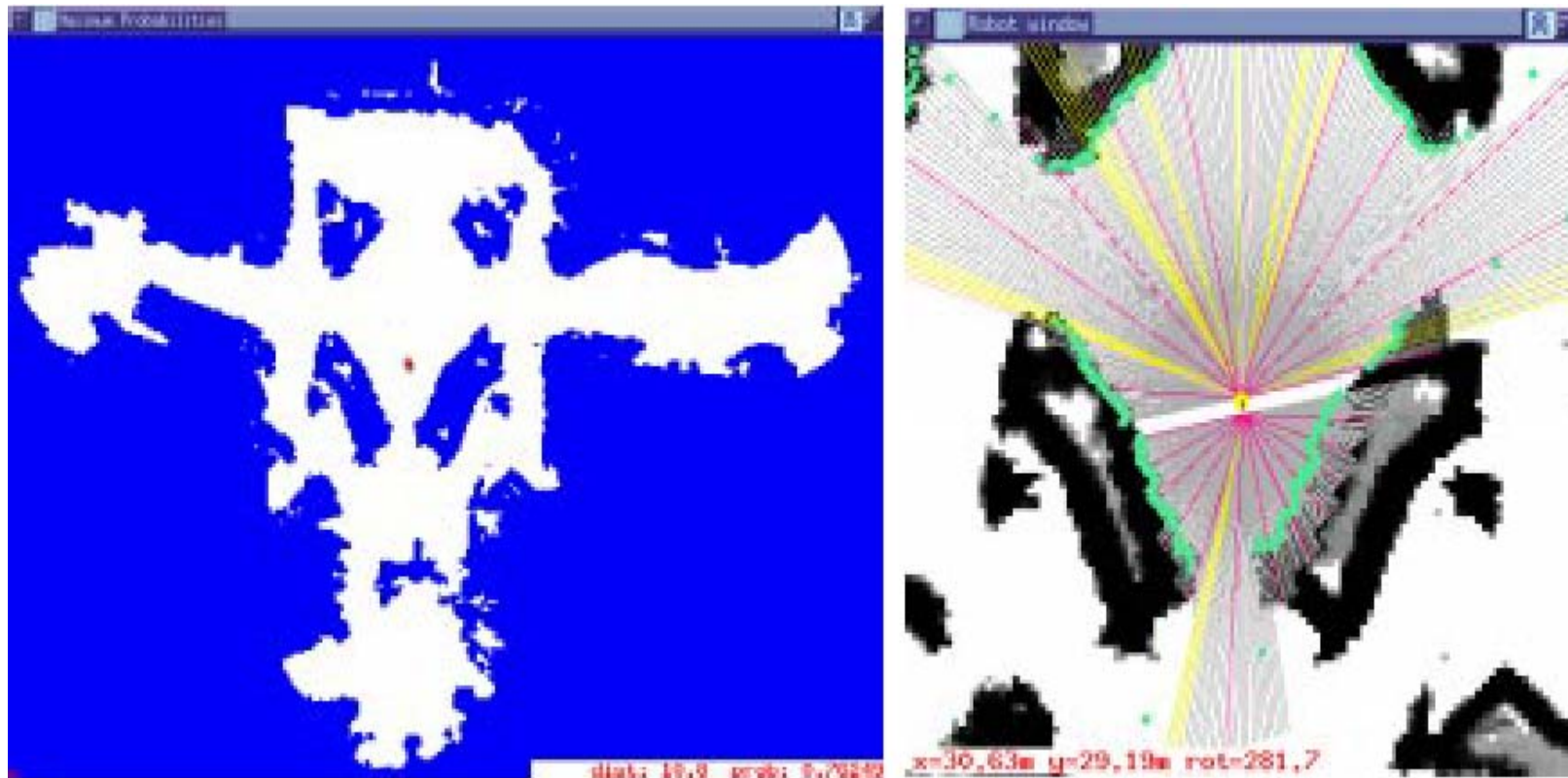


Markov Localization

Case Study – Grid Map

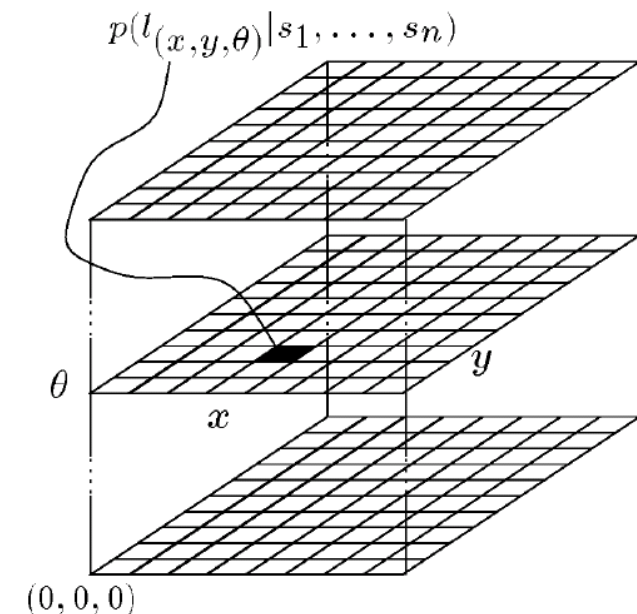
*Courtesy of
W. Burgard*

- Example 2: Museum
 - Laser scan 21



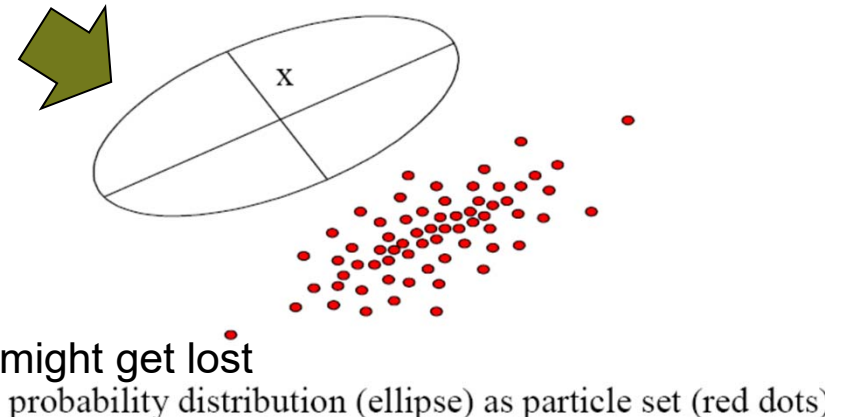
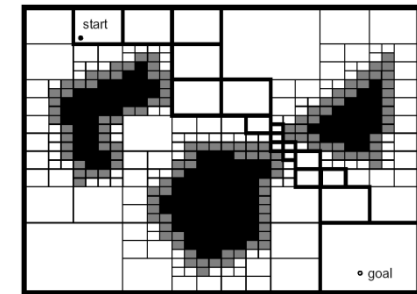
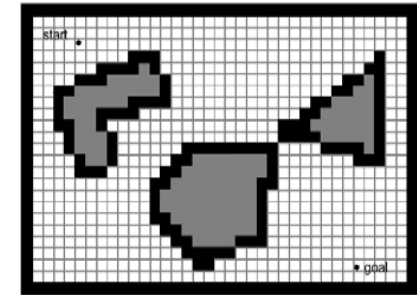
Drawbacks of Markov localization

- Planar motion case
 - is a three-dimensional grid-map array
 - cell size must be chosen carefully.
- During each prediction and measurement steps
 - all the cells are updated
 - the computation can become too heavy for real-time operations.
- Example
 - 30x30 m environment;
cell size of 0.1 m x 0.1 m x 1 deg
 - $300 \times 300 \times 360 = 32.4$ million cells!
 - Important processing power needed
 - Large memory requirement



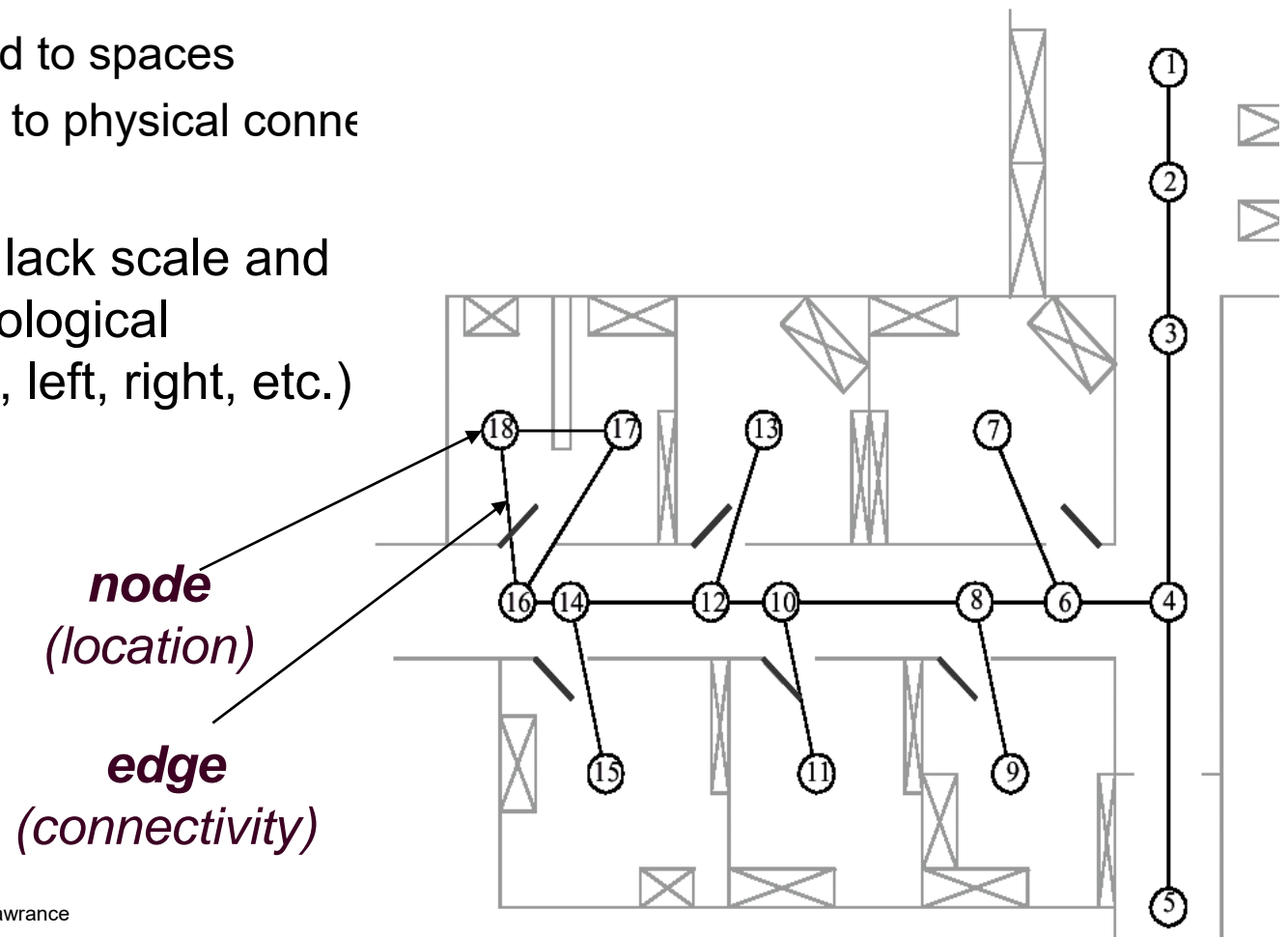
Drawbacks of Markov localization

- Reducing complexity
 - Various approaches have been proposed for reducing complexity
 - One possible solution would be to increase the cell size at the expense of localization accuracy.
 - Another solution is to use an adaptive cell decomposition instead of a fixed cell decomposition.
- Randomized Sampling / **Particle Filter**
 - The main goal is to reduce the number of states that are updated in each step
 - Approximated belief state by representing only a '**representative**' subset of all states (possible locations)
 - E.g. update only 10% of all possible locations
 - The sampling process is **typically weighted**, e.g. put more samples around the local peaks in the probability density function
 - However, you have to ensure some less likely locations are still tracked, otherwise the robot might get lost



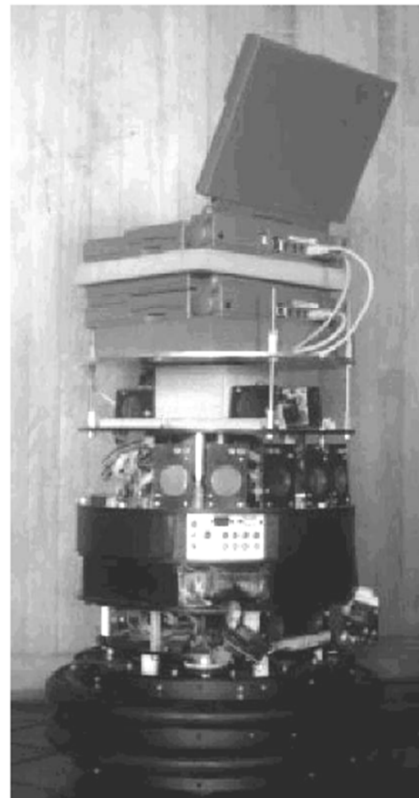
Map Representation | *Topological map*

- A topological map represents the environment as a graph with nodes and edges.
 - Nodes correspond to spaces
 - Edge correspond to physical connections
- Topological maps lack scale and distances, but topological relationships (e.g., left, right, etc.) are maintained



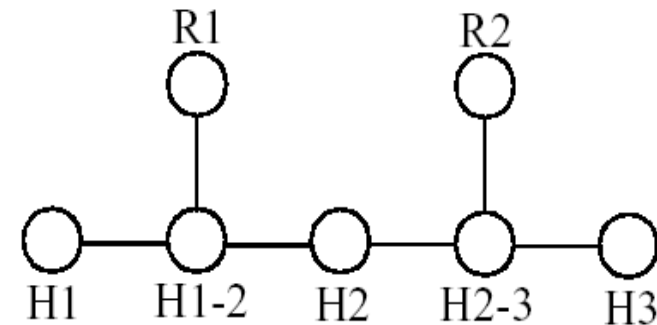
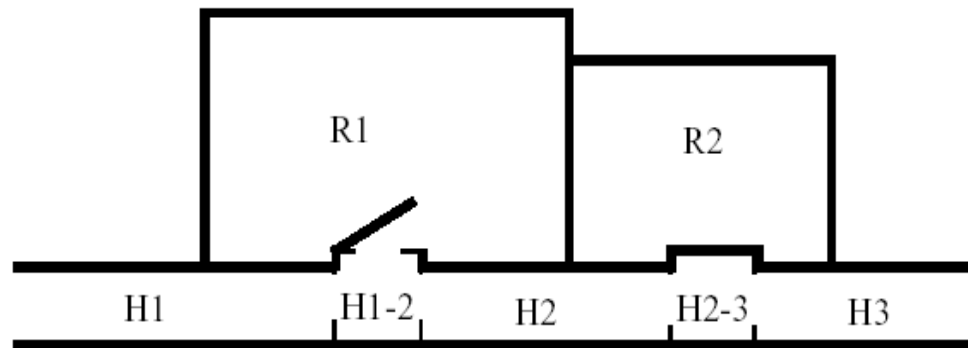
Markov Localization: *Case Study - Topological Map (1)*

- The Dervish Robot
- Topological Localization



Markov Localization: Case Study - Topological Map (2)

- Topological map of office-type environment



	Wall	Closed door	Open door	Open hallway	Foyer
Nothing detected	0.70	0.40	0.05	0.001	0.30
Closed door detected	0.30	0.60	0	0	0.05
Open door detected	0	0	0.90	0.10	0.15
Open hallway detected	0	0	0.001	0.90	0.50

Markov Localization: Case Study - Topological Map (3)

- Update of believe state for position n given the percept-pair i

$$p(n|i) = p(i|n)p(n)$$

- $p(n|i)$: new likelihood for being in position n
- $p(n)$: current believe state
- $p(i|n)$: probability of seeing i in n (see table)

	Wall	Closed door	Open door	Open hallway	Foyer
Nothing detected	0.70	0.40	0.05	0.001	0.30
Closed door detected	0.30	0.60	0	0	0.05
Open door detected	0	0	0.90	0.10	0.15
Open hallway detected	0	0	0.001	0.90	0.50

- No action update !

- However, the robot is moving and therefore we can apply a combination of action and perception update

$$p(n_t|i_t) = \int p(n_t|n'_{t-i}, i_t)p(n'_{t-i})dn'_{t-i}$$

- $t-i$ is used instead of $t-1$ because the topological distance between n' and n is very depending on the specific topological map

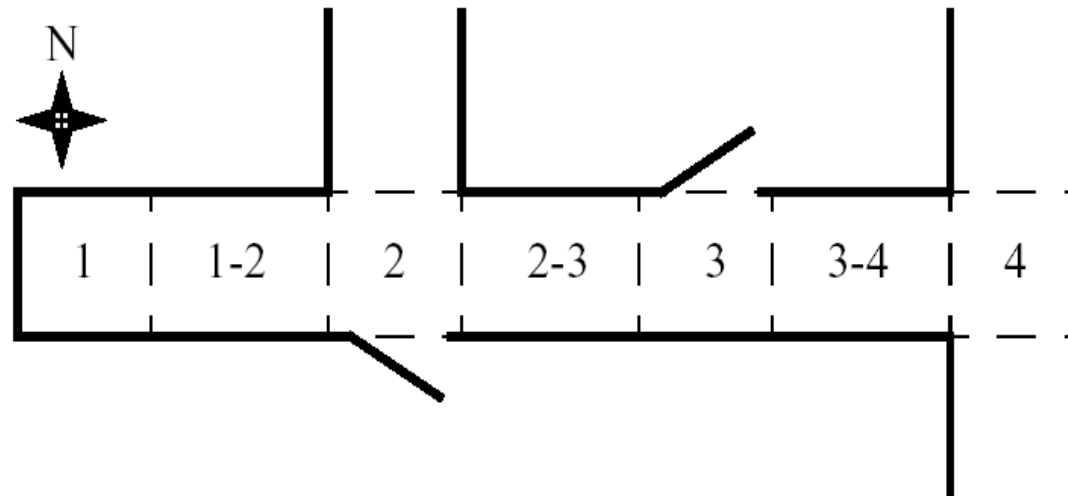
Markov Localization: Case Study - Topological Map (4)

- The calculation

$$p(n_t | n'_{t-i}, i_t)$$

is realized by multiplying the probability of generating perceptual event i at position n by the probability of having failed to generate perceptual event s at all nodes between n' and n .

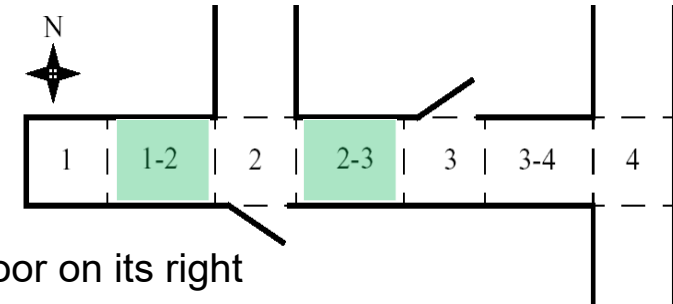
$$p(n_t | n'_{t-i}, i_t) = p(i_t, n_t) \cdot p(\emptyset, n_{t-1}) \cdot p(\emptyset, n_{t-2}) \cdot \dots \cdot p(\emptyset, n_{t-i+1})$$



Markov Localization: Case Study - Topological Map (5)

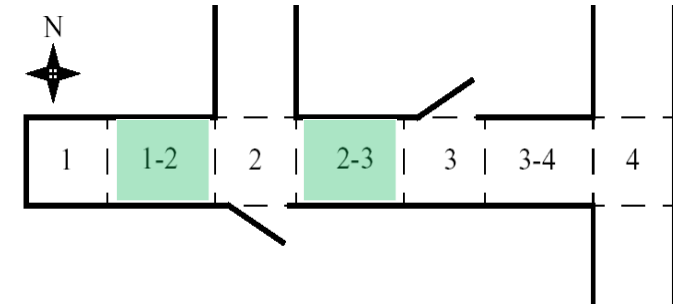
Example calculation

- Assume that the robot has two nonzero belief states
 - $p(1-2) = 1.0$; $p(2-3) = 0.2^*$
 and that it is facing east with certainty
- Perceptual event:** open hallway on its left and open door on its right
- State 2-3 will progress potentially to 3, 3-4 or 4.
- State 3 and 3-4 can be eliminated because the likelihood of detecting an open door is zero.
- The likelihood of reaching state 4 is the product of the initial likelihood $p(2-3) = 0.2$, (a) the likelihood of detecting anything at node 3 and the likelihood of detecting a hallway on the left and a door on the right at node 4 and (b) the likelihood of detecting a hallway on the left and a door on the right at node 4. (for simplicity we assume that the likelihood of detecting nothing at node 3-4 is 1.0)
- (a) occurs only if Dervish fails to detect the door on its left at node 3 (either closed or open), $[0.6 \cdot 0.4 + (1-0.6) \cdot 0.05]$ and correctly detects nothing on its right, **0.7**.
- (b) occurs if Dervish correctly identifies the open hallway on its left at node 4, **0.90**, and mistakes the right hallway for an open door, **0.10**.
- This leads to:
 - $0.2 \cdot [0.6 \cdot 0.4 + 0.4 \cdot 0.05] \cdot 0.7 \cdot [0.9 \cdot 0.1] \rightarrow p(4) = 0.003.$
 - Similar calculation for progress from 1-2 $\rightarrow p(2) = 0.3.$



	Wall	Closed door	Open door	Open hallway	Foyer
Nothing detected	0.70	0.40	0.05	0.001	0.30
Closed door detected	0.30	0.60	0	0	0.05
Open door detected	0	0	0.90	0.10	0.15
Open hallway detected	0	0	0.001	0.90	0.50

Markov Localization: Case Study - Topological Map (5)



	Wall	Closed door	Open door	Open hallway	Foyer
Nothing detected	0.70	0.40	0.05	0.001	0.30
Closed door detected	0.30	0.60	0	0	0.05
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