Modern Robot Mapping

Research Qualifier

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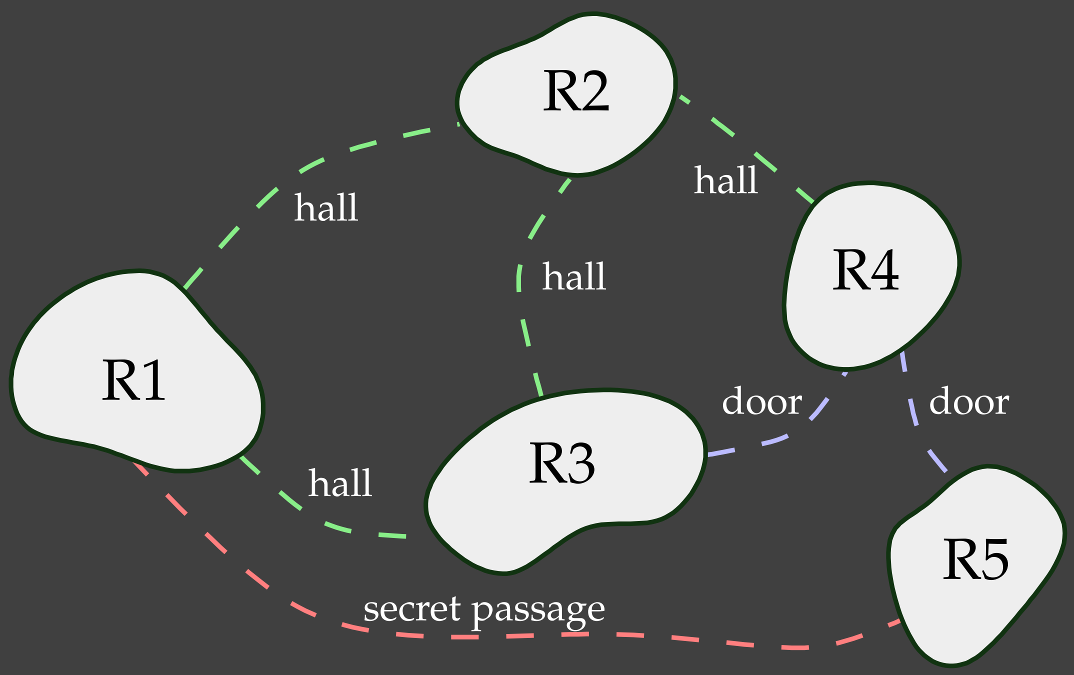
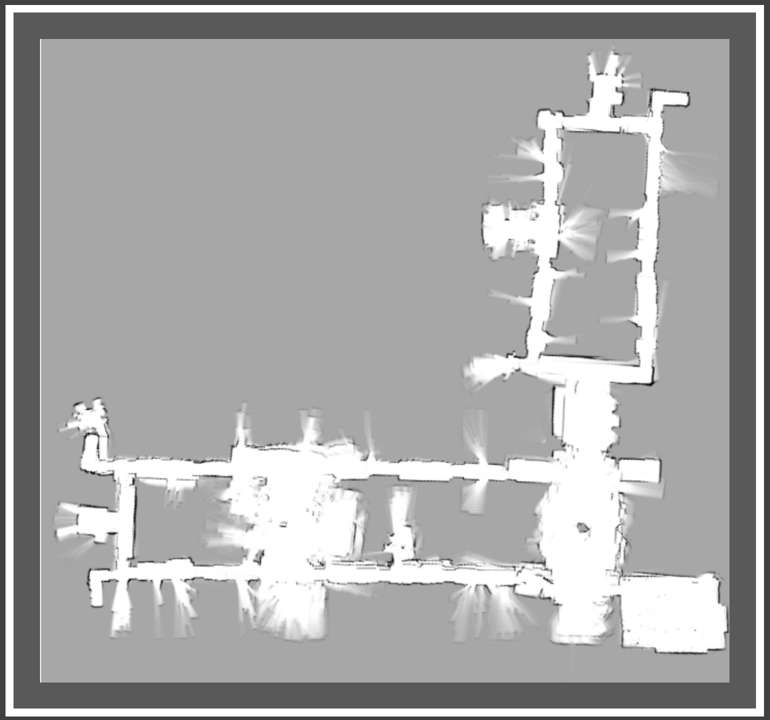
Robot mapping

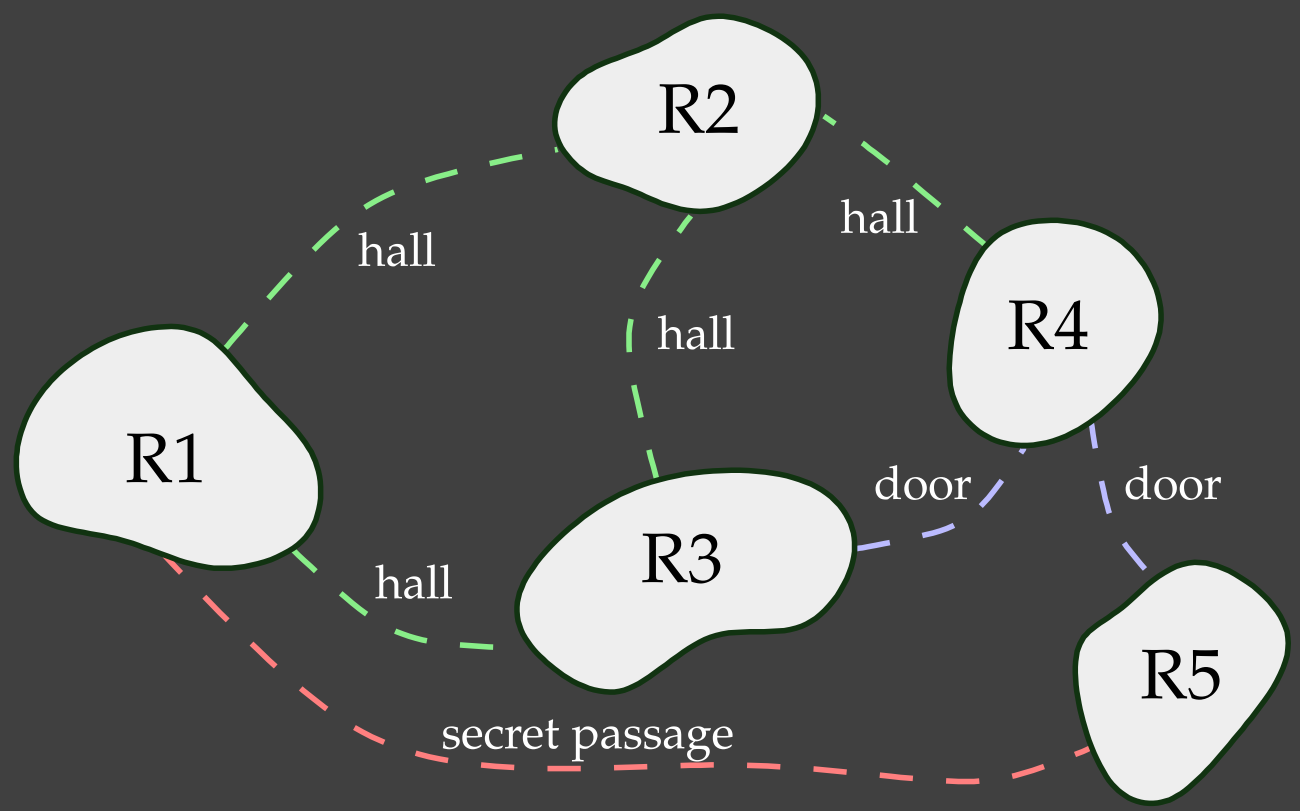


Topological

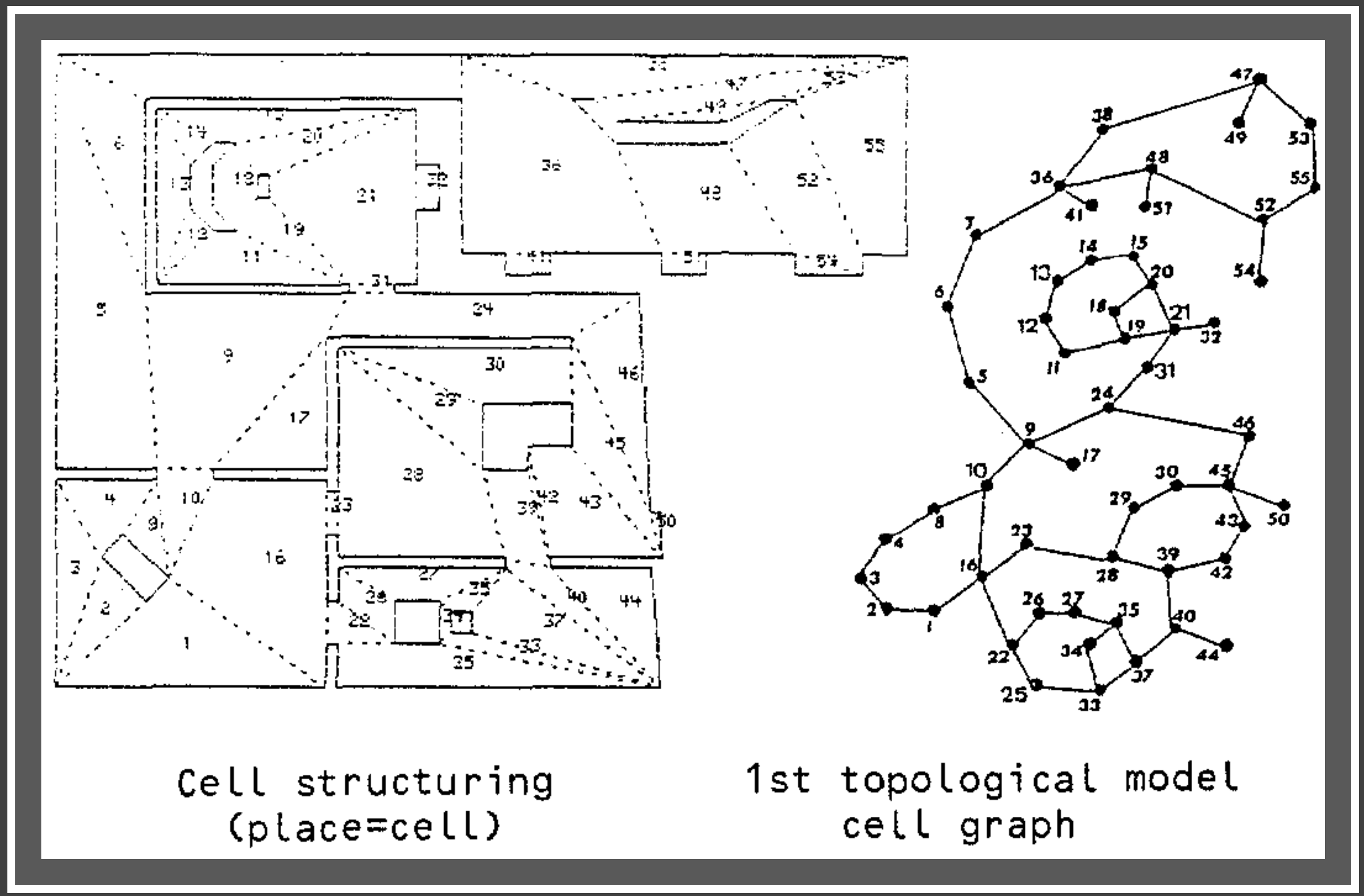


Geometrical

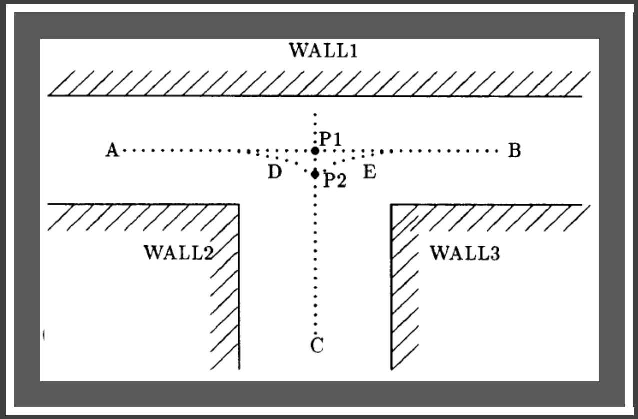
Topological maps

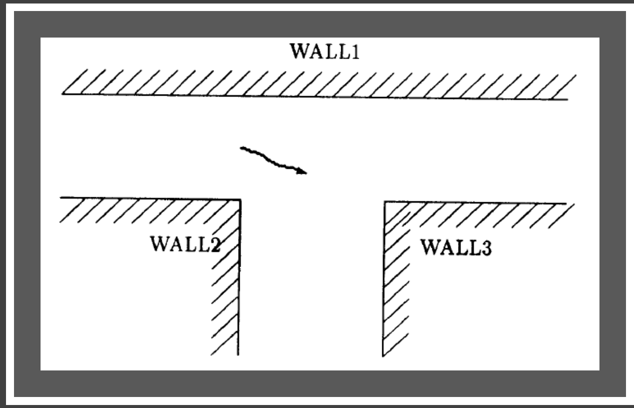


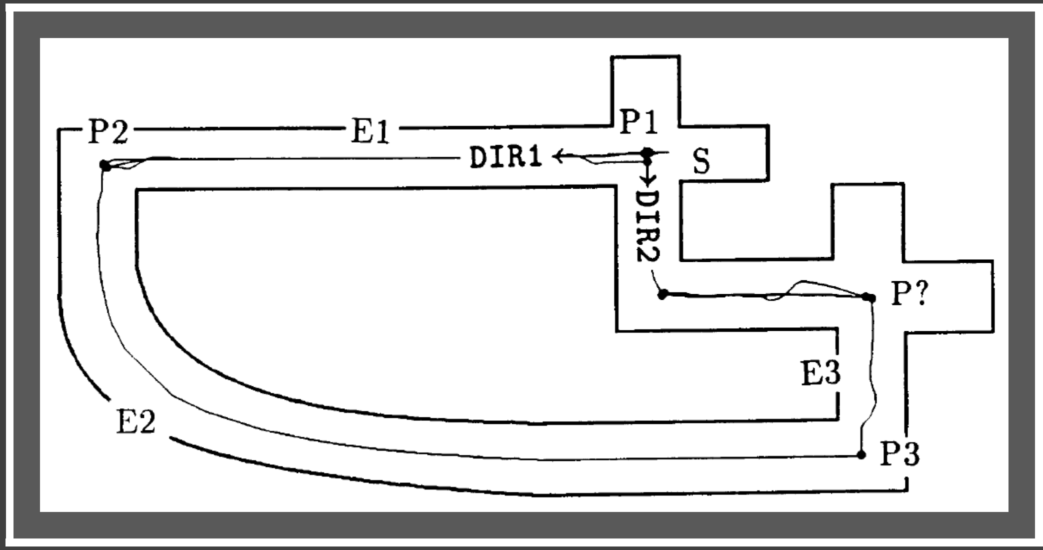
Chatila and Laumond (1985)



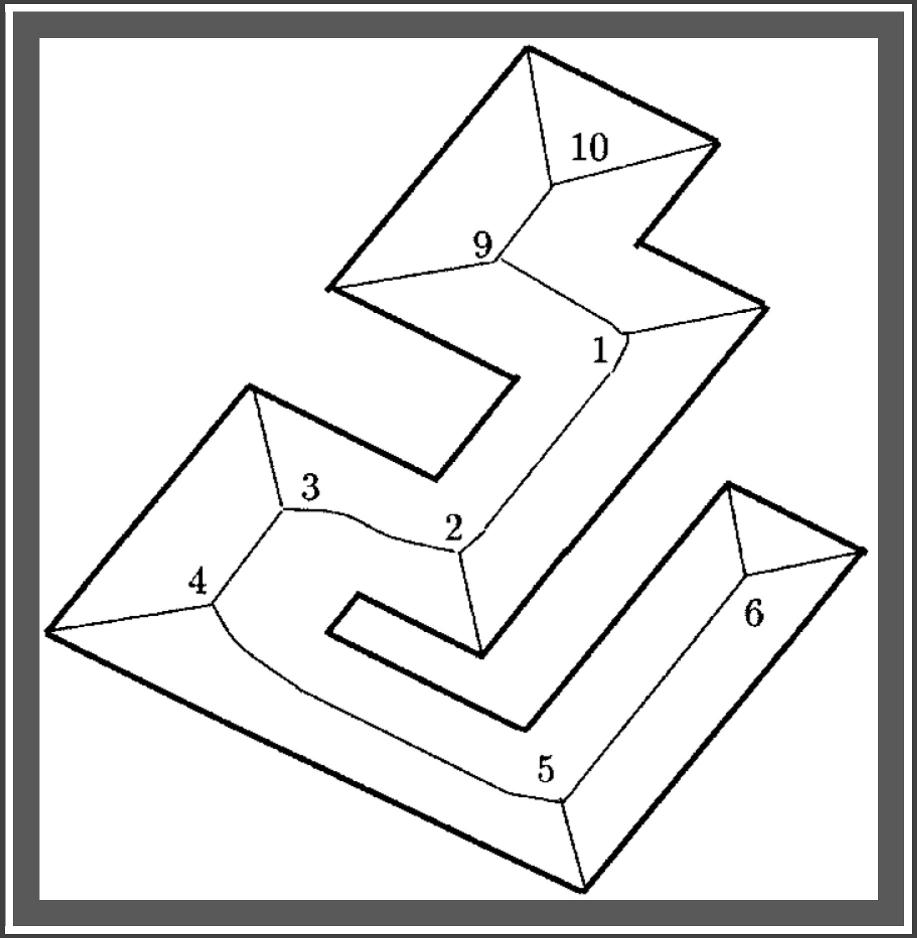
Kuipers and Byun (1991)



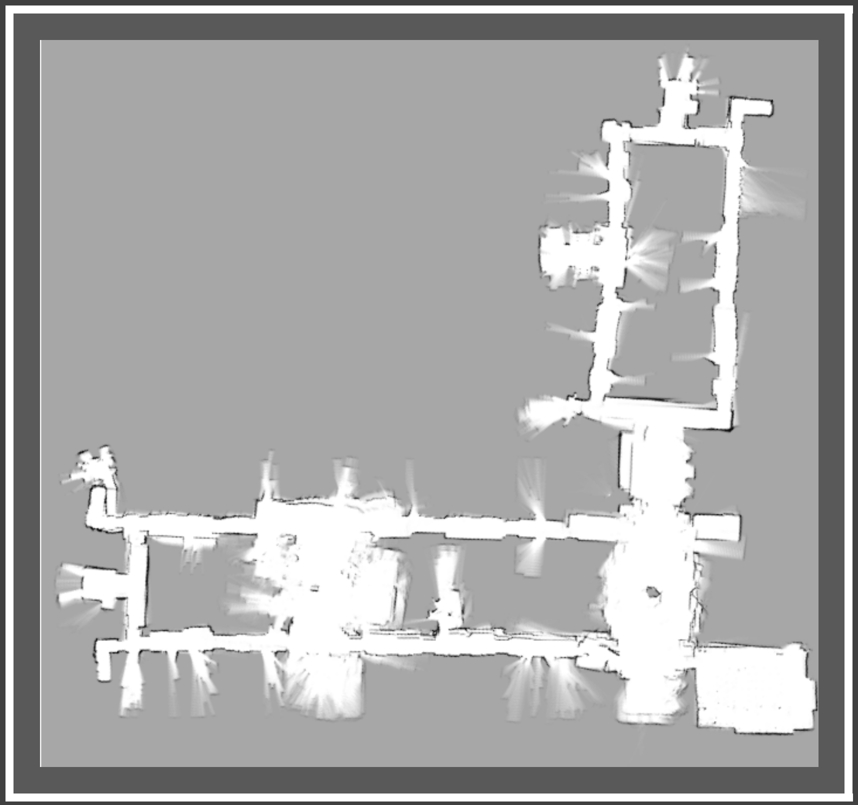




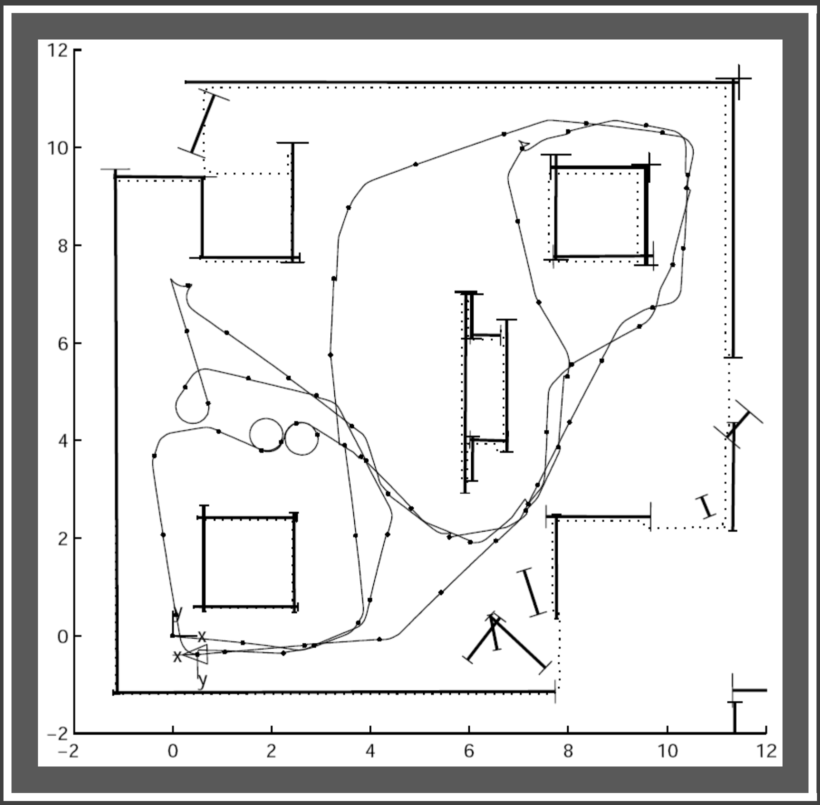
Choset and Nagatani (2001)



Geometrical maps (SLAM)

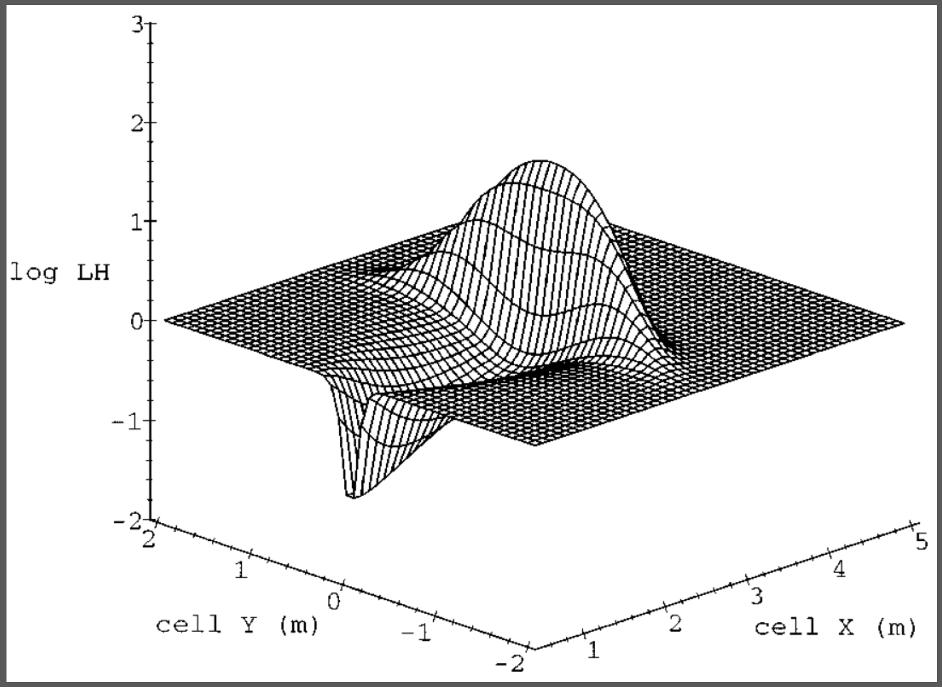


Occupancy grid

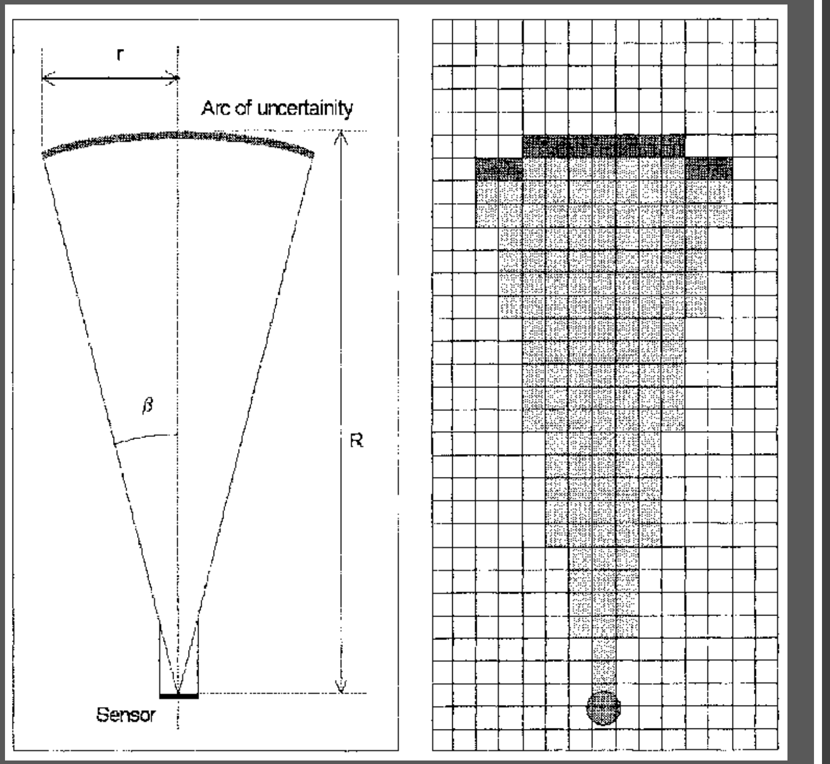


Landmark

Occupancy sensor models



Konolige (1997)



Pagac et al. (1998)

Smith et al. (1990)

The *stochastic map*:

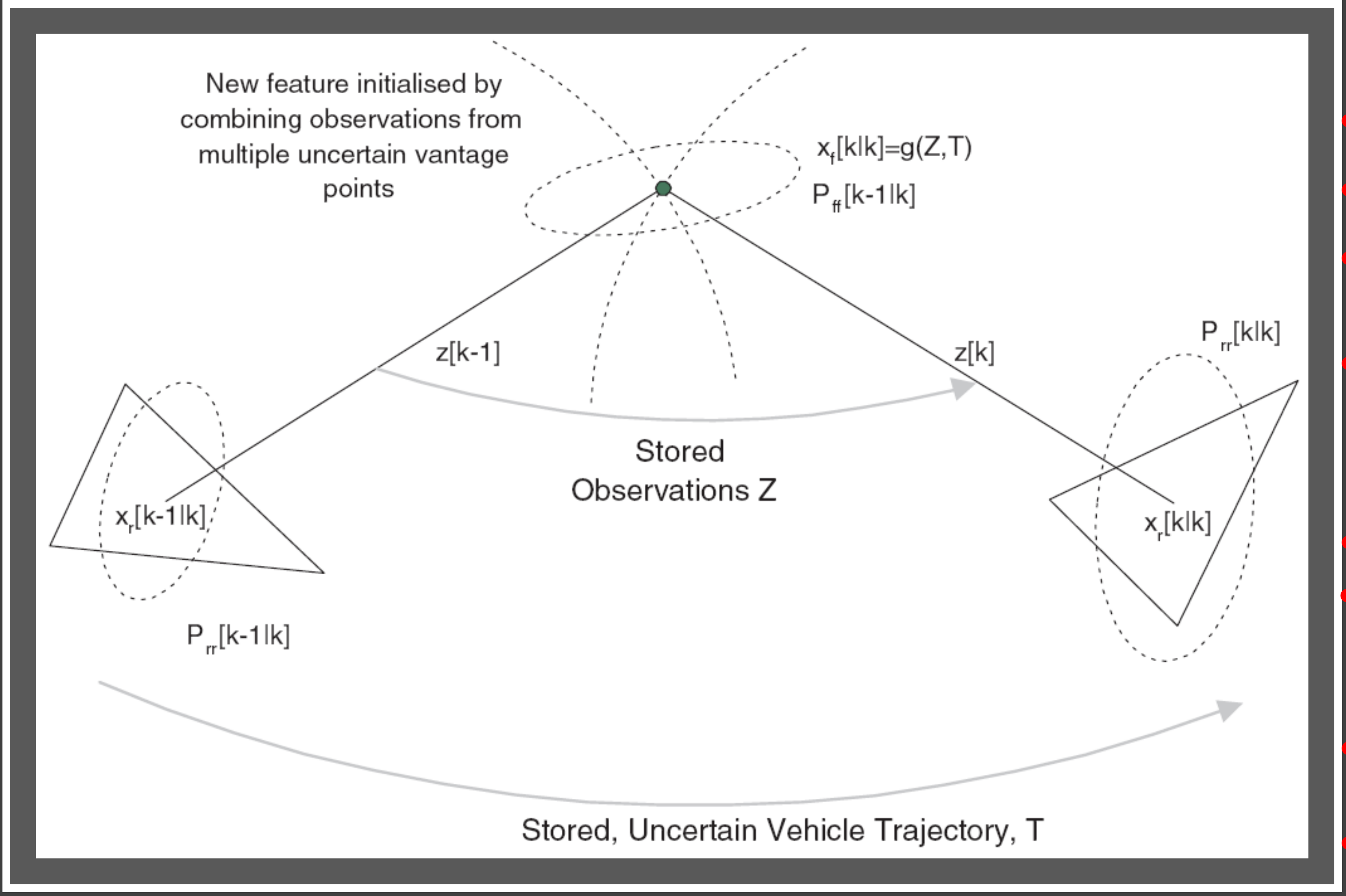
$$\mathbf{x} = \begin{bmatrix} \mathbf{x}_1 \\ \mathbf{x}_2 \\ \vdots \\ \mathbf{x}_N \end{bmatrix} \quad C(\mathbf{x}) = \begin{bmatrix} C(\mathbf{x}_1) & C(\mathbf{x}_1, \mathbf{x}_2) & \cdots & C(\mathbf{x}_1, \mathbf{x}_N) \\ C(\mathbf{x}_2, \mathbf{x}_1) & C(\mathbf{x}_2) & \cdots & C(\mathbf{x}_2, \mathbf{x}_N) \\ \vdots & \vdots & \ddots & \vdots \\ C(\mathbf{x}_N, \mathbf{x}_1) & C(\mathbf{x}_N, \mathbf{x}_2) & \cdots & C(\mathbf{x}_N) \end{bmatrix}$$

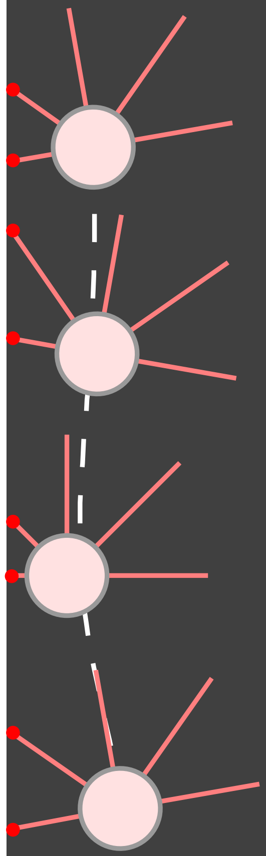
- Updates using the Kalman filter or EKF
- Ignore data association

Cox and Leonard (1994)

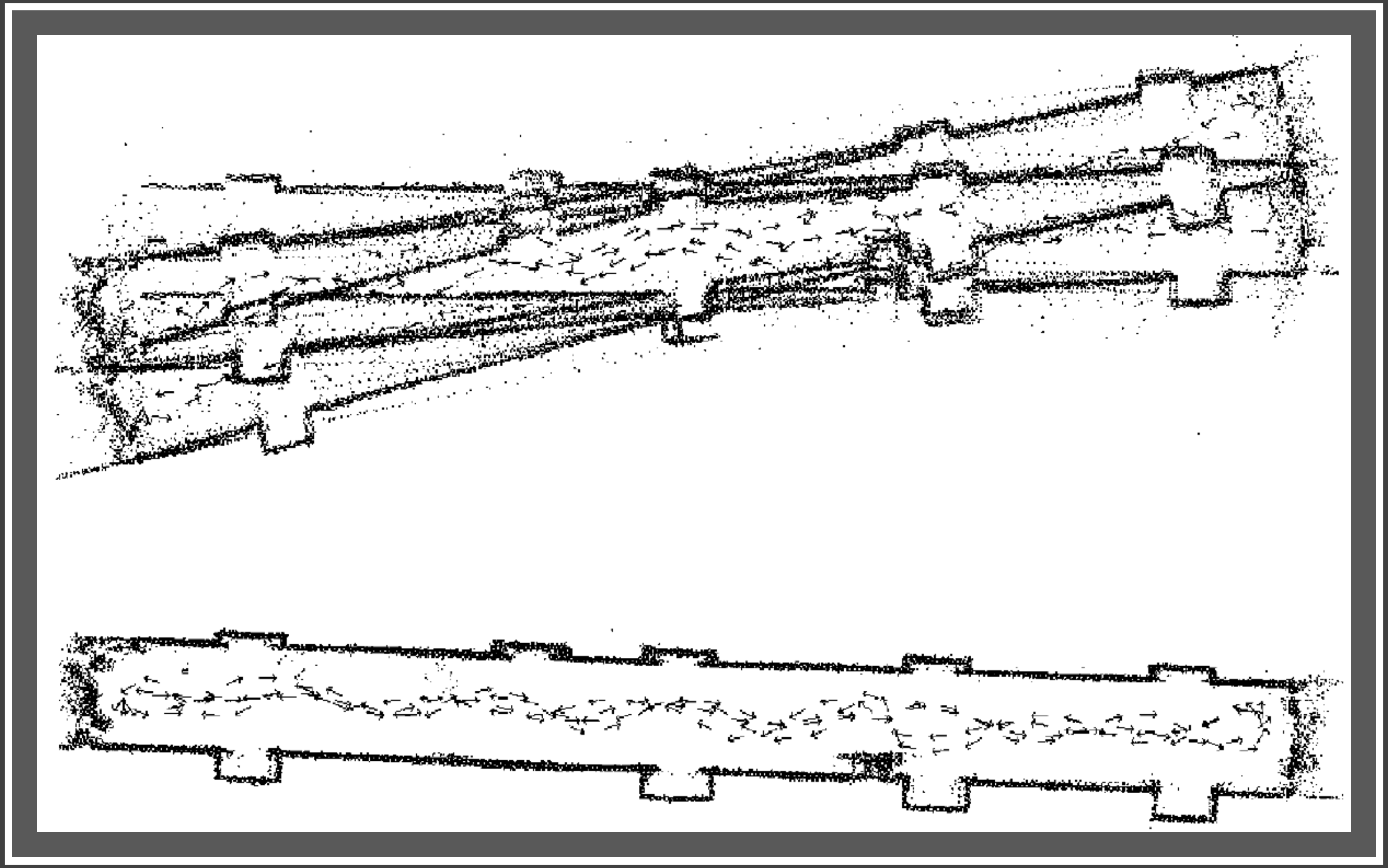
- Data association uncertainty $\neq$ sensing uncertainty
- Hypothesis tree: branches $\equiv$ different assignments of measurements to landmarks
- “Deterministic FastSLAM”

Leonard et al. (2002)

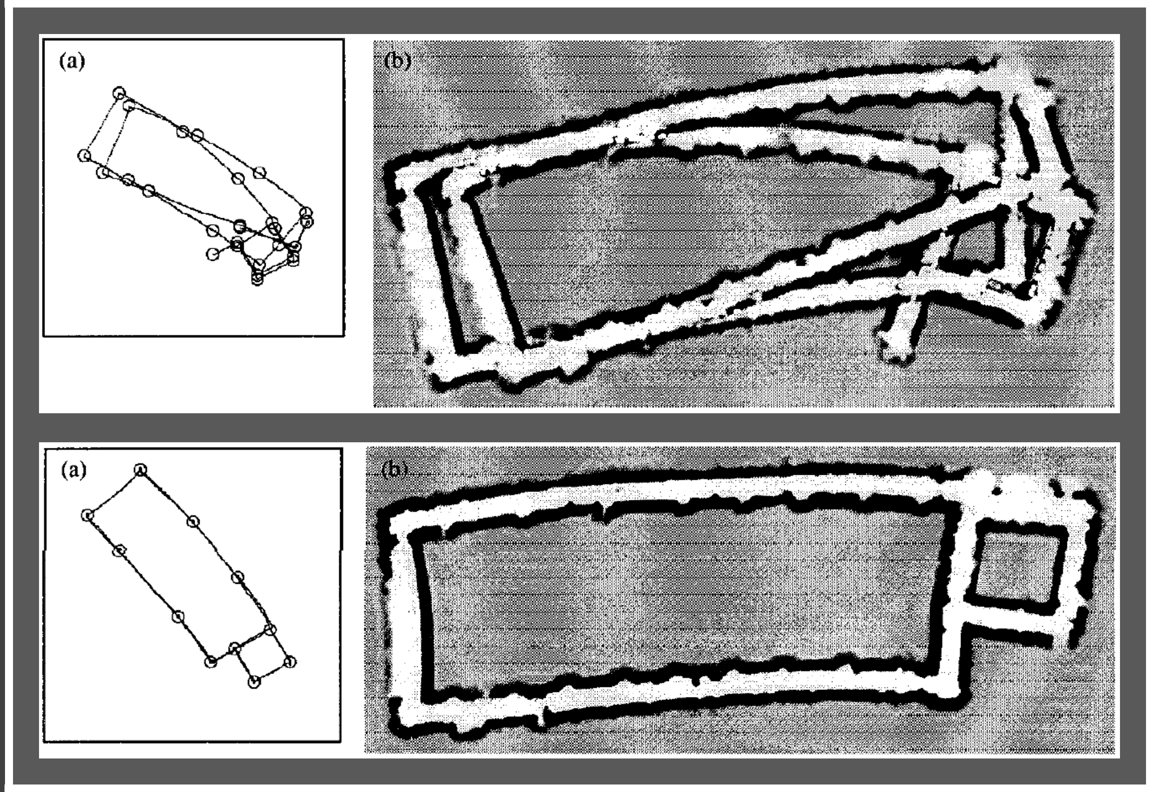




Lu and Milios (1997)

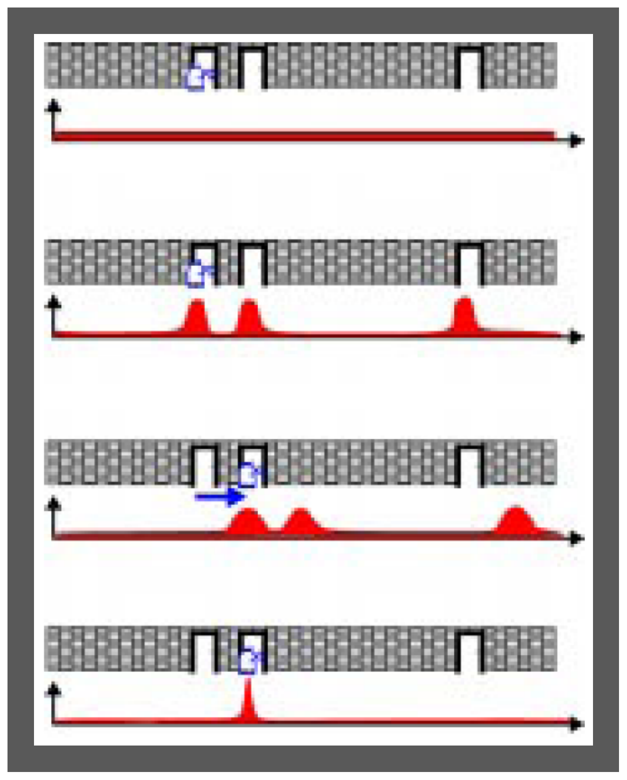


Thrun et al. (1998)



E-step (localize), M-step (expand map)

Fox et al. (1999)



- Grid representation of pdfs
- *Markov assumption* (static world): measurements depend only on current pose

$\hookrightarrow$ known path/map $\Rightarrow$ future measurements independent of past measurements

Murphy (2000)

- Under Markov assumption, landmarks are independent when **conditioned on trajectory**

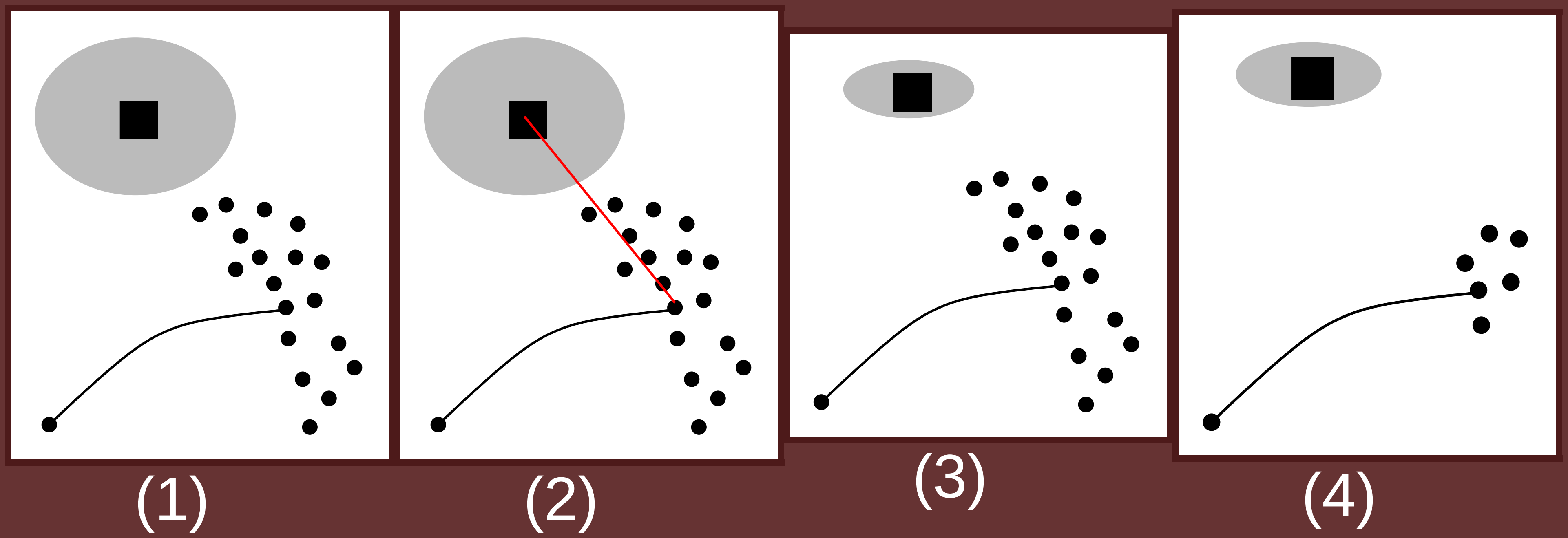
- Factor the map posterior (Rao-Blackwellization):

$$p(s^t, \Theta) = p(s^t) \prod_{n=1}^{N} p(\theta_n | s^t)$$

- Many small filters

Thrun et al. (2004): FastSLAM

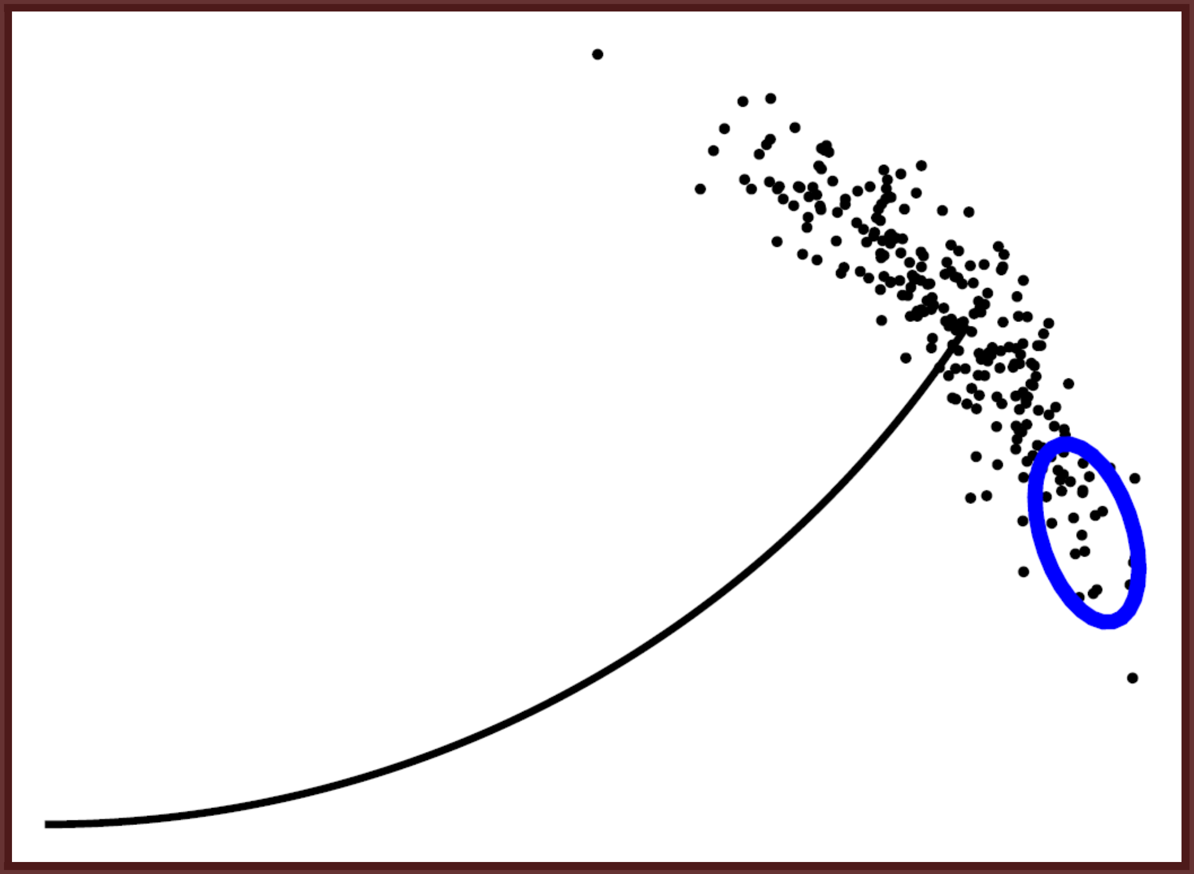
Algorithm



Per-particle data association

- Different assignments of measurements to landmarks for each particle
- Multiple data association hypotheses
- Recall (Cox and Leonard, 1994)

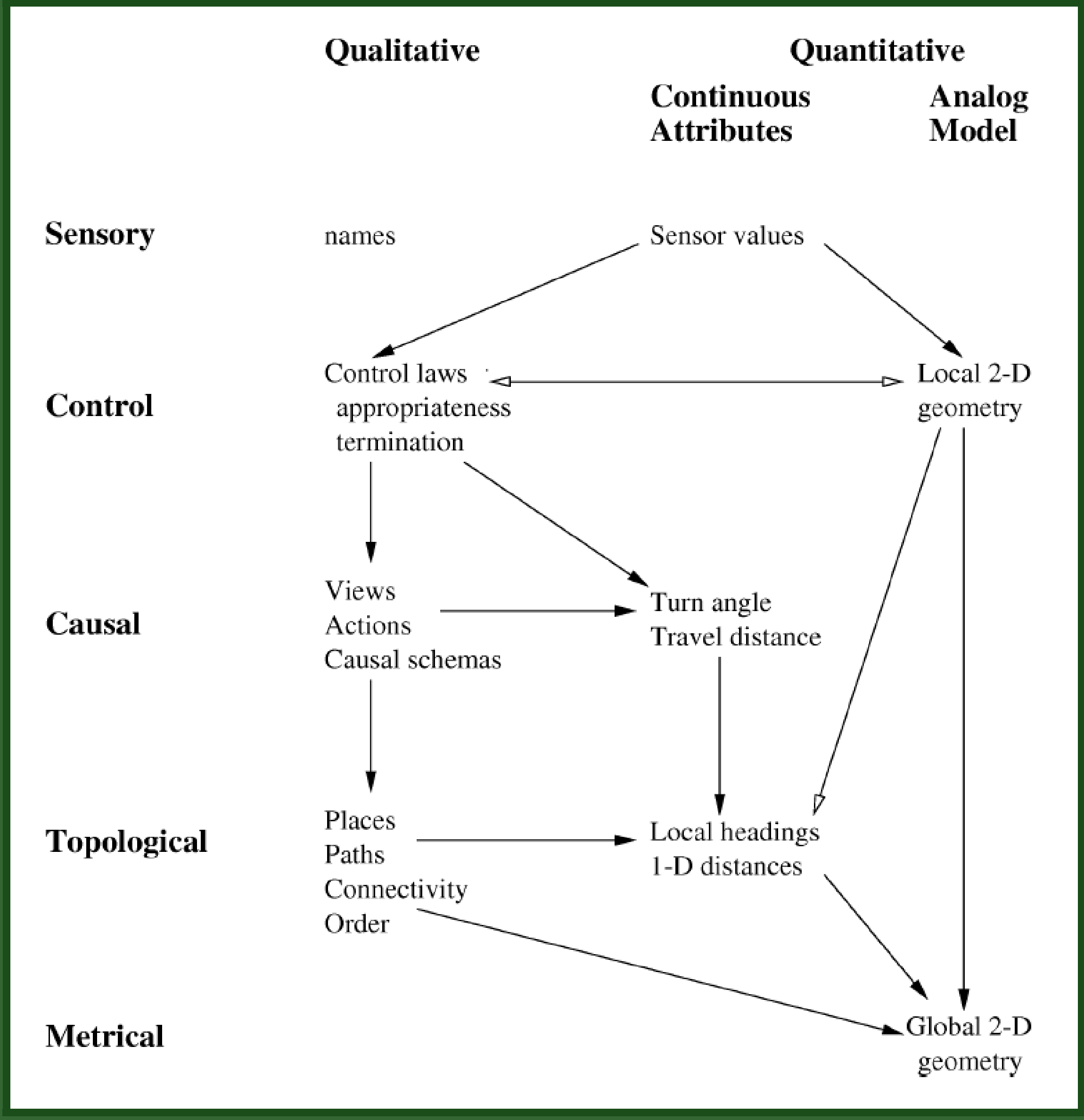
FastSLAM 2.0



Convergence

- Converges for linear Gaussian models
- No better SLAM convergence result is known
- **Q**: does FastSLAM converge for nonlinear, non-Gaussian models?
- **Q**: how many particles to converge?

Kuipers (2000):
Spatial semantic hierarchy


Qualitative
Quantitative
Continuous Attributes
Analog Model
Sensory
names
Sensor values
Control
Control laws
appropriateness
termination
Local 2-D geometry
Causal
Views
Actions
Causal schemas
Turn angle
Travel distance
Topological
Places
Paths
Connectivity
Order
Local headings
1-D distances
Metrical
Global 2-D geometry

Loop closing in SSH

- “Rehearsal”: active graph matching
- Recognized by Kuipers as the weakest link

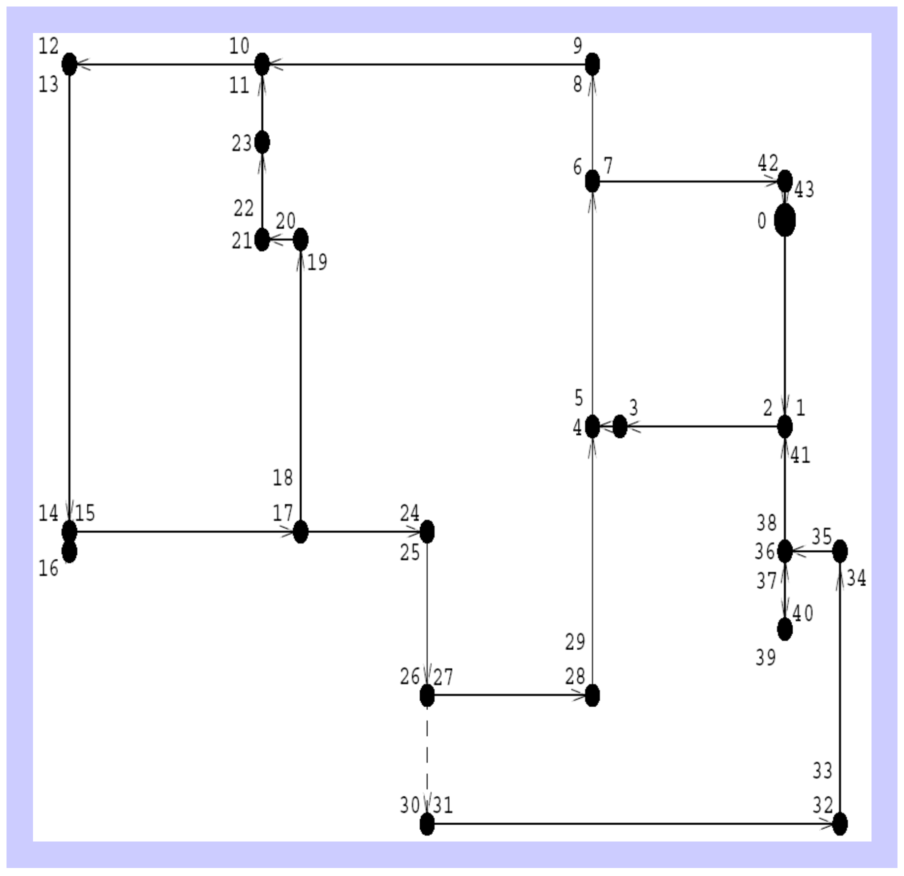
$\hookrightarrow$ “effective but ad hoc”

$\hookrightarrow$ decisions? self-similarity? **uncertainty?**

$\hookrightarrow$ “should perhaps be replaced by a more principled POMDP-based strategy”

Shatkay and Kaelbling (2002): Geometrically constrained HMMs

Topological map as HMM



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HMMS VS. POMDPS

- HMM:

↪ hidden state, transitions
↪ passive (no decision about where to go next)

- POMDP:

↪ hidden state, transitions
↪ controlled (robot decides where to explore)
↪ computes tradeoff between **reward** (map expansion) and **uncertainty** (map accuracy)

HMMS with geometry

- Learning HMMS: evidence $\equiv$ observations at states

$\hookrightarrow$ "sensing signatures"

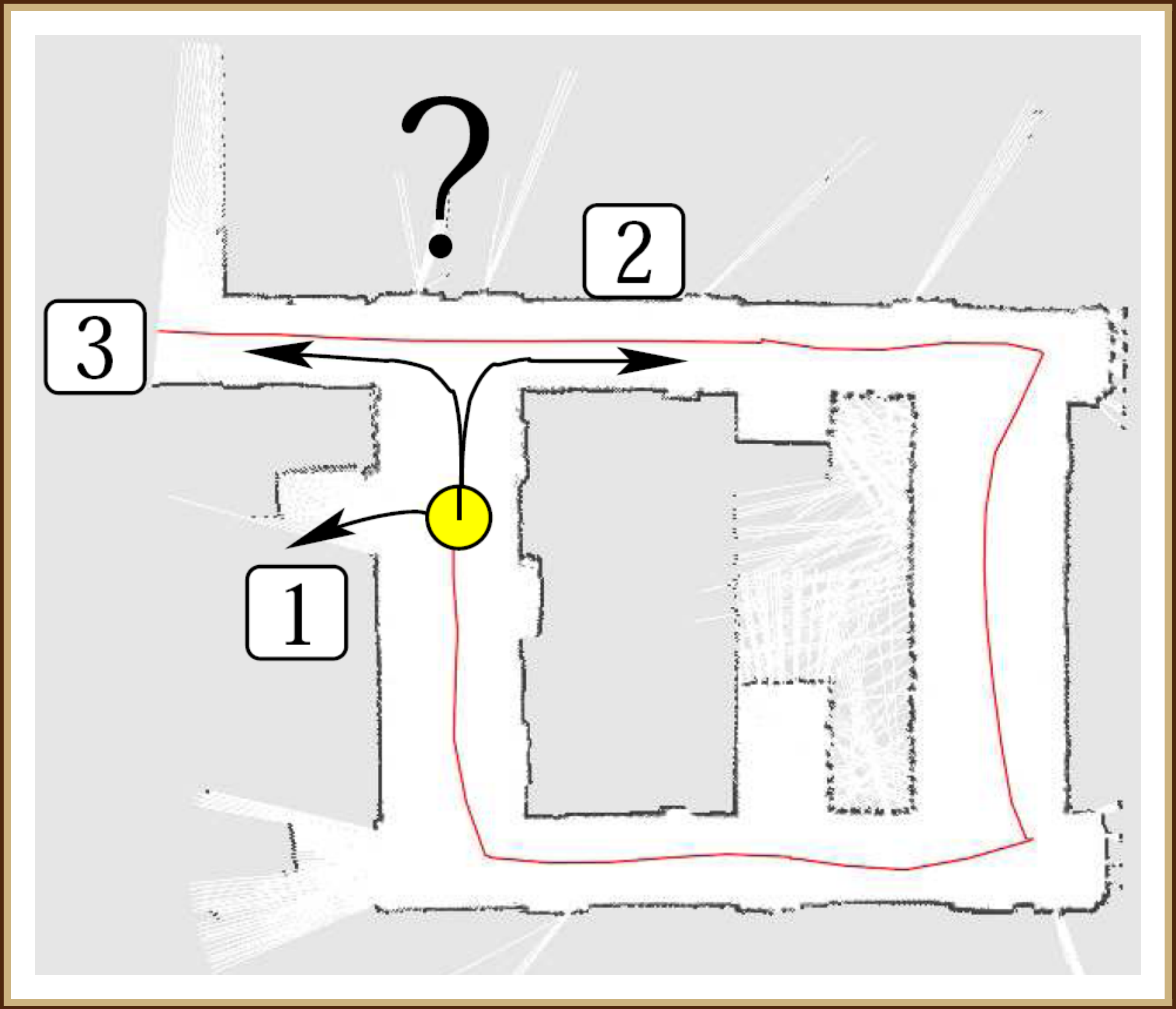
- Why not incorporate odometry information?

$\hookrightarrow$ HMMS augmented with geometric relationships
$\hookrightarrow$ consistency enforced

- Faster convergence, better accuracy

- Requires major assumptions: **# states known**

Stachniss et al. (2005): Information-gain based exploration



Exploration
vs.
Accuracy

Cost
vs.
Utility

Utility: Information gain

- Pick action that minimizes cost and maximizes information

$\hookrightarrow$ like a POMDP with one-step lookahead

- Maximizing information $\equiv$ minimizing entropy

$$H(p(s^t|\text{data})) + \sum_i p(s_i^t|\text{data}) \cdot H(\Theta_i|s_i^t, \text{data})$$

Details

- Approximating information gain is hard

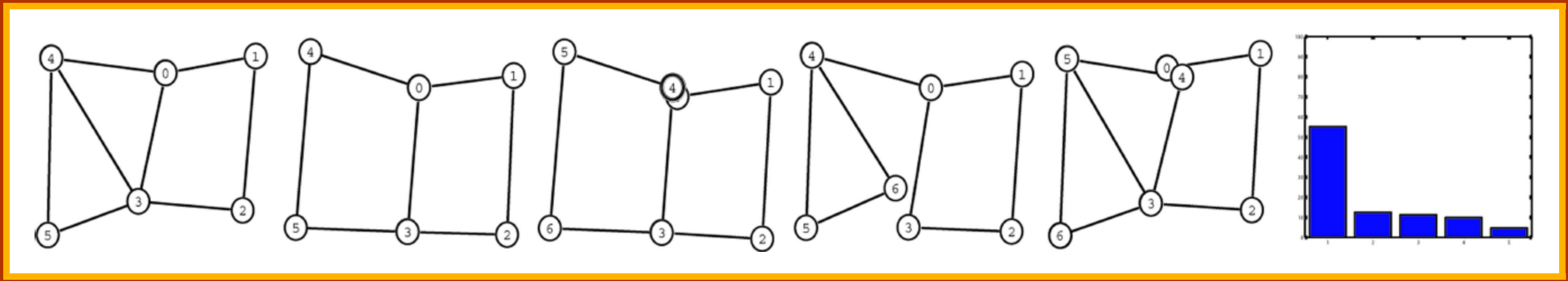
$\hookrightarrow$ averaging of pose entropies in trajectories

$\hookrightarrow$ ray casting over expected action trajectory to approximate measurements and guess change in map

$\hookrightarrow$ statistics for unexplored cells

- Actions: exploration, revisiting, loop-closing

Ranganathan et al. (2005): Topological mapping as Bayesian inference



Inference in the space of topologies:

1: Start with valid topologies T_i
2: **for** each measurement **do**
3:     **for all** samples **do**
4:         Propose new topology T_i'
5:         Compute likelihood $p(T_i'|\text{data})$
6:     Resample based on likelihood

Details

- Space of topologies $\equiv$ set partitions of measurements

- Proposal distribution: split or merge nodes

- Requires known priors:

$\hookrightarrow$ locations of distinctive places
$\hookrightarrow$ topologies / # of places

Prognostication

- Has been: topological **or** geometrical
- Will be: topological **and** geometrical

$\hookrightarrow$ topometrical?
$\hookrightarrow$ metrilogical?

Thank you!

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