CS354

JAMES MADISON UNIVERSITY®

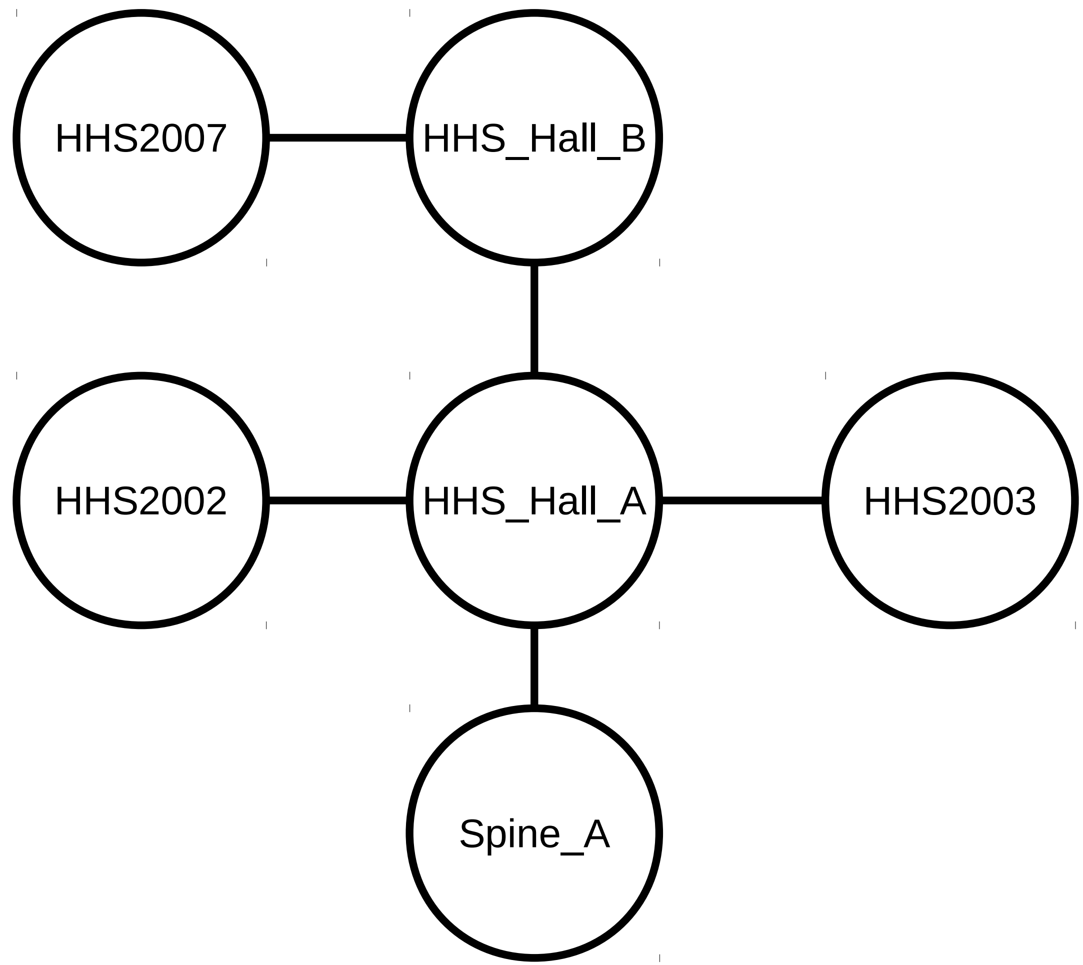
Representing Maps: Topological

- Represent relative locations using a graph structure.

  + Good for high level navigation

  - Difficult to build autonomously

  - Not good for low-level localization and navigation



Representing Maps: Geometric Landmark Based

- Store the geometric location of recognizable landmarks.
  - Maybe artificial beacons or markers.
  - Maybe distinctive environmental features.

+ Memory-efficient

+ Allows precise localization

- Landmark mis-identification can cause problems

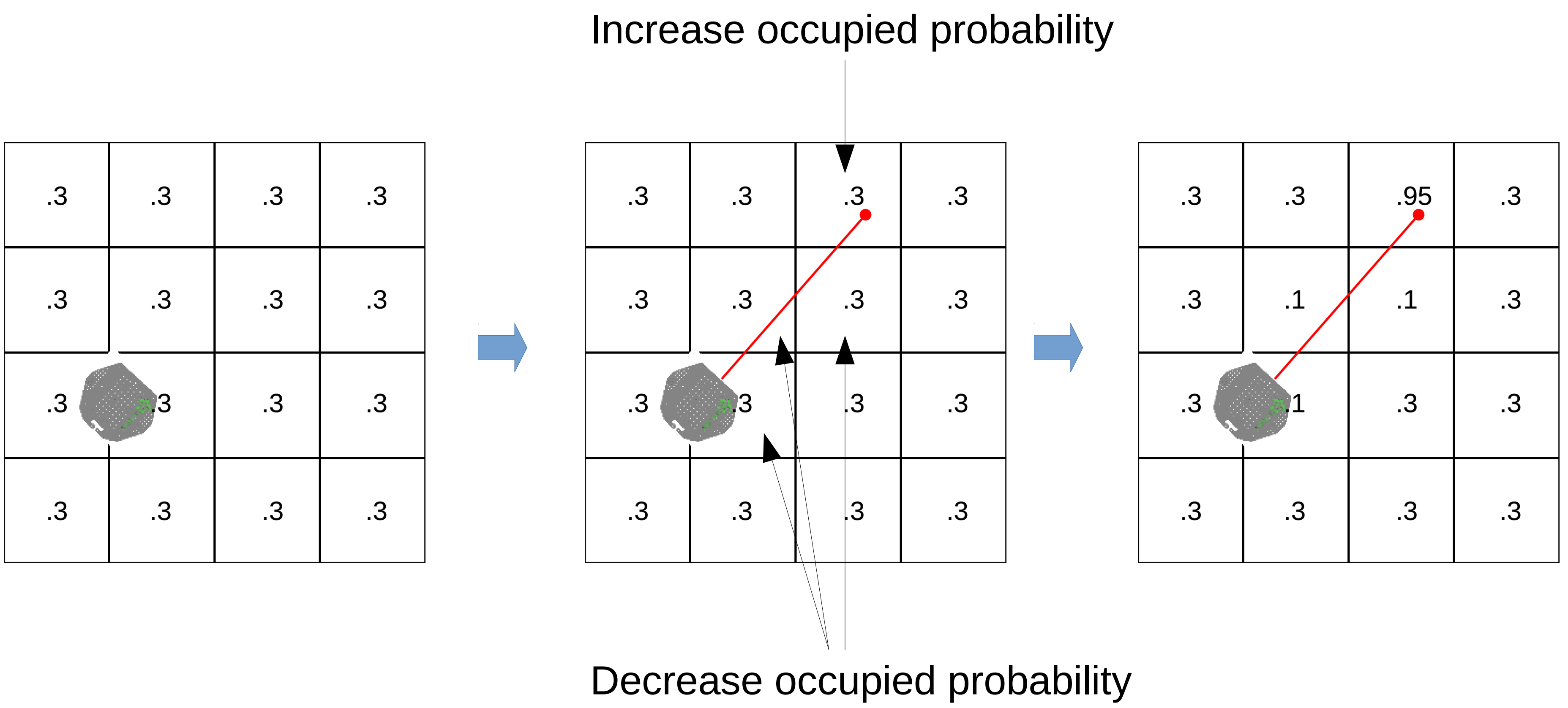
- May not be ideal for identification: only landmark positions are stored, not necessarily the positions of all obstacles

Representing Maps: Occupancy Grid

- Divide the environment into grid cells, maintain an "occupied" probability for each cell.
  - Memory intensive (particularly in 3D)
  + Good for navigation
  + Good for localization
  + Relatively simple to create autonomously

Mapping w/ Occupancy Grids

- Relatively easy if we know the robot pose:



SLAM – Simultaneous Localization and Mapping

- Recall the localization problem:

$$P(\mathbf{x}_t | \mathbf{z}_{0:t}, \mathbf{u}_{0:t})$$

- The SLAM problem is reassuringly familiar:

$$P(\mathbf{x}_t, \Theta | \mathbf{z}_{0:t}, \mathbf{u}_{0:t})$$

- Where Θ represents the map.
- Before we wanted a probability distribution over all possible robot poses.
- Now we want a joint probability distribution over all possible robot poses and all possible maps.

  "Distribution over possible maps" is not as manageable as "distribution over poses"

SLAM "Solution"

- Prediction:

$$Bel^{-}(\mathbf{x}_t, \Theta) = \int P(\mathbf{x}_t \mid \mathbf{x}_{t-1}, \mathbf{u}_t) Bel(\mathbf{x}_{t-1}, \Theta) d\mathbf{x}_{t-1}$$

- Correction:

$$Bel(\mathbf{x}_t, \Theta) = \eta P(\mathbf{z}_k \mid \mathbf{x}_t, \Theta) Bel^{-}(\mathbf{x}_t, \Theta)$$

- The tricky bit is correction: updating the distribution over pose and map estimates given sensor data

Adapted from Simultaneous Localisation and Mapping (SLAM): Part 1 The Essential Algorithms, Hugh Durrant-Whyte, 2006

(Extended) Kalman Filter SLAM

- Most appropriate for landmark-based map.
- Let's look at the example from the textbook.
- Problems:
  - Not clear how to use this for occupancy grids
  - The covariance matrix gets really big as the number of landmarks grows

Particle Filter SLAM: Problems

- Covering the space of possible poses and maps with particles is not practical:
  - "Pose particle": 3-6 dimensions
  - "Map particle" for a (tiny) 10x10 grid: 100 dimensions
  - Joint map x pose particle: 300-600 dimensions

Rao-Blackwellized Particle Filter

- Solution/Approximation:
  - Each pose particle has an associated map.
  - Each map is updated under the assumption that its particle represents the correct pose.
  - The map may be landmark-based or occupancy grid-based.
- The ROS gmapping package uses this approach