COS 495 - Lecture 13
Autonomous Robot Navigation

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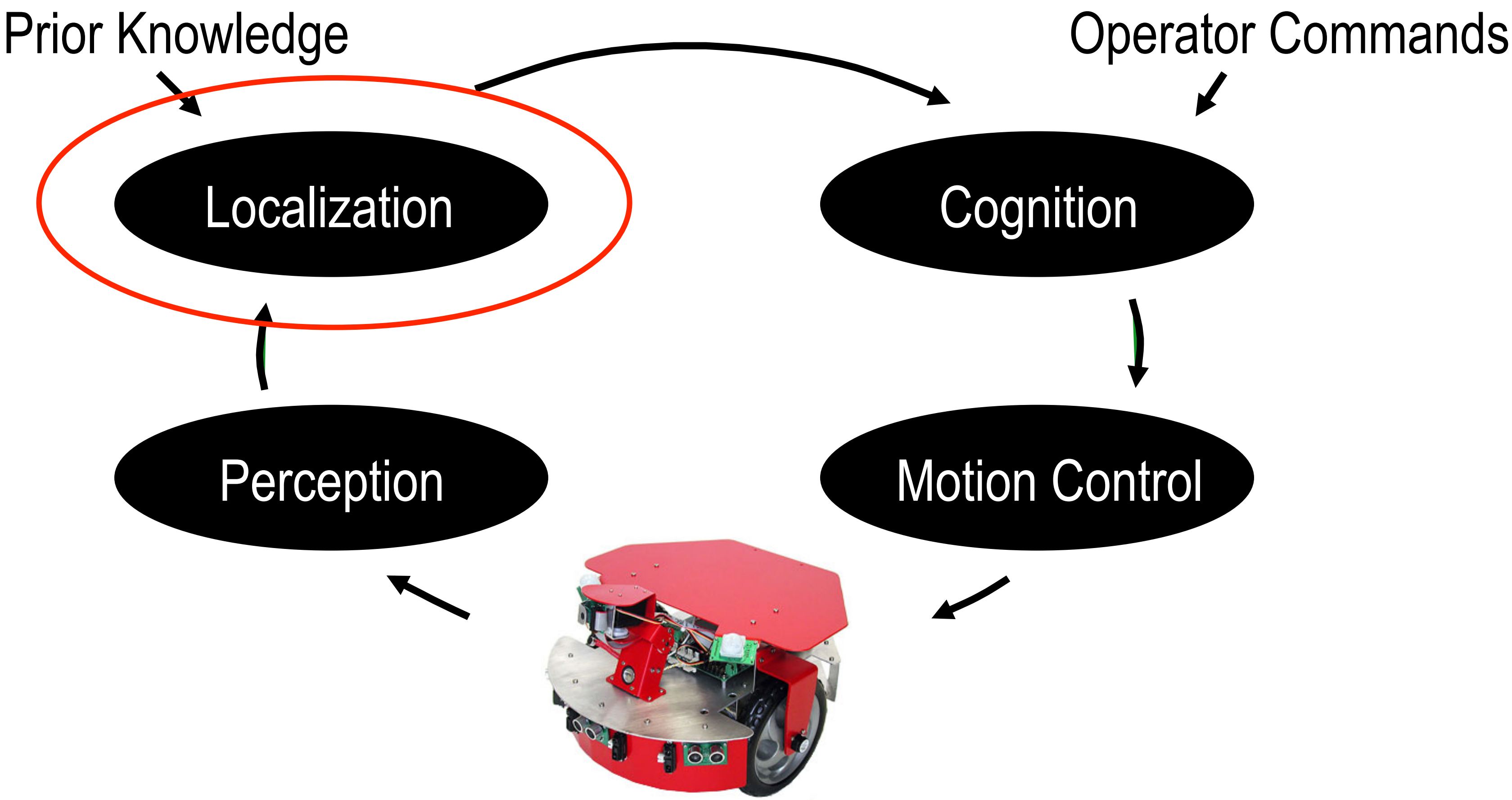
Semester: Fall 2011

Figures courtesy of Siegwart & Nourbakhsh

Control Structure

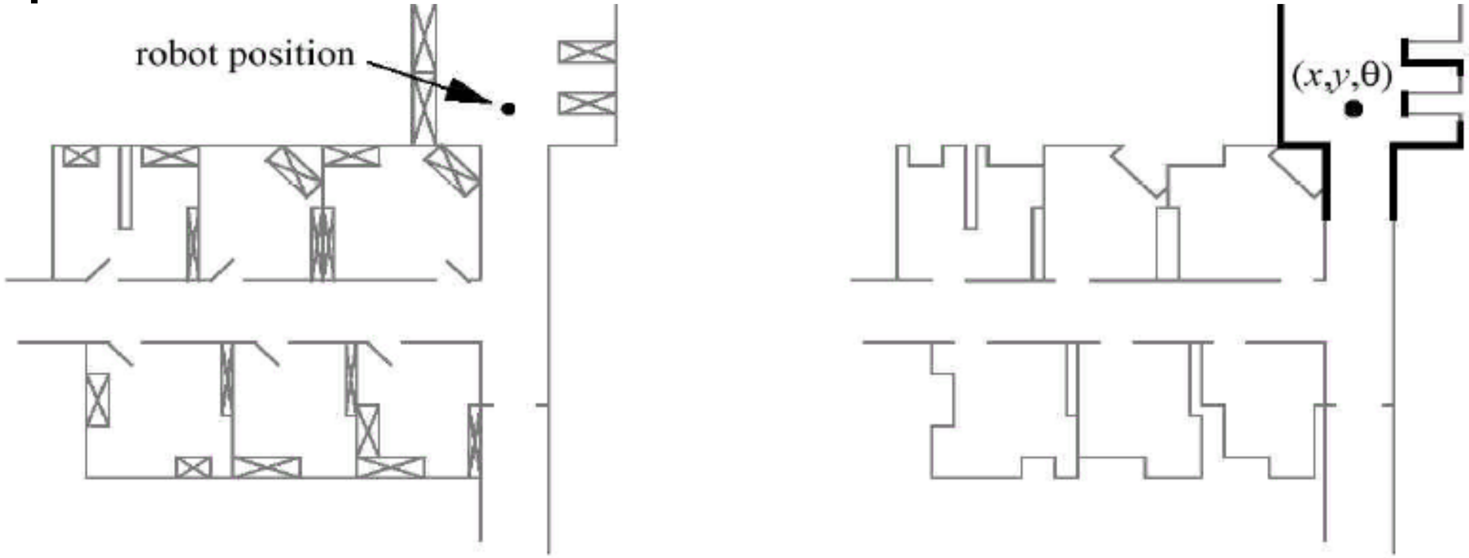


Localization: Outline

1. Localization Tools
    1. Belief representation
    2. Map representation
    3. Probability Theory
2. Overview of Algorithms

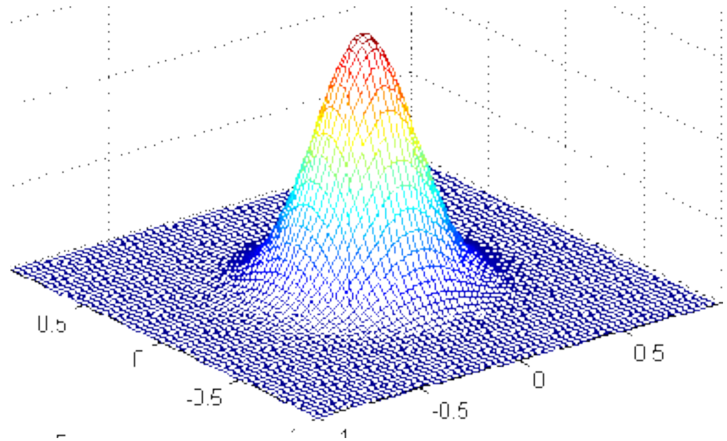
Belief Representation

- Our belief representation refers to the method we describe our estimate of the robot state.
- So far we have been using a *Continuous* Belief representation.



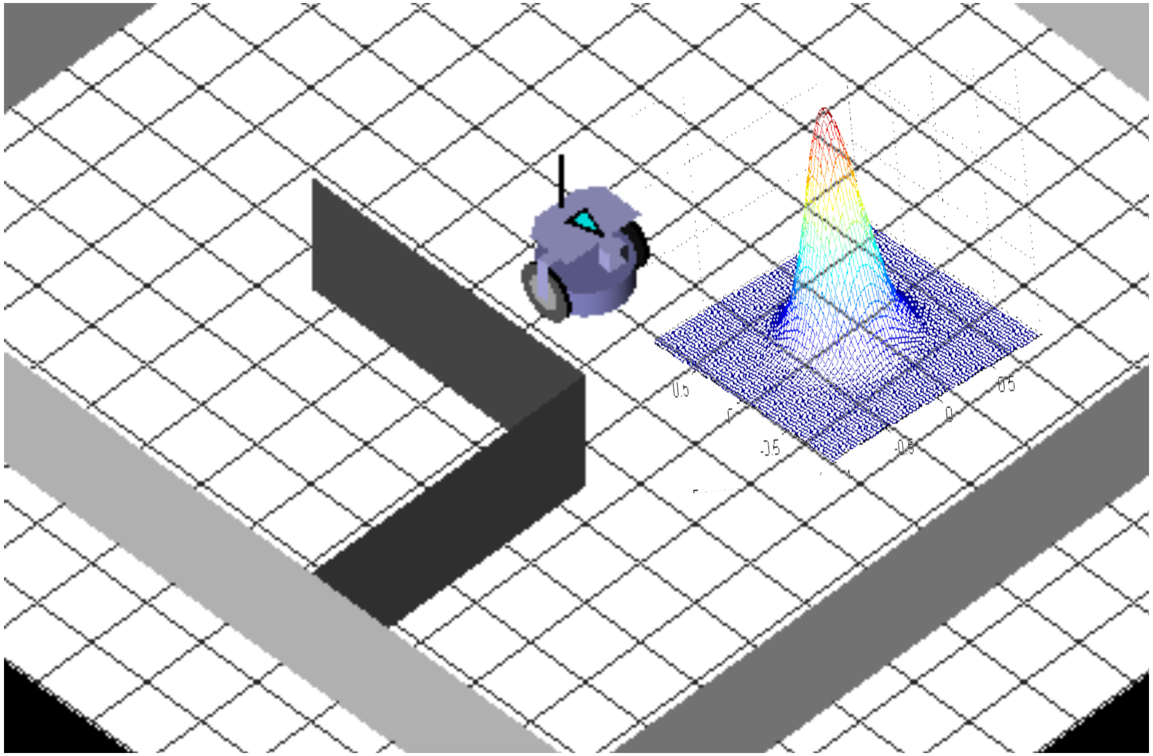
Belief Representation

- We can provide a description of the level of confidence we have in our estimate.
- We typically use a Gaussian distribution to model the state of the robot.
- We need to know the variance of this Gaussian!



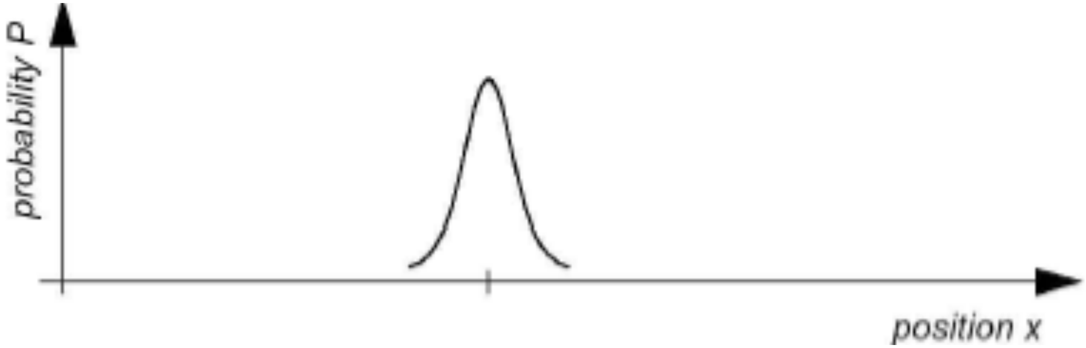
Belief Representation

- For example, consider modeling our robot's position with a 2D Gaussian:

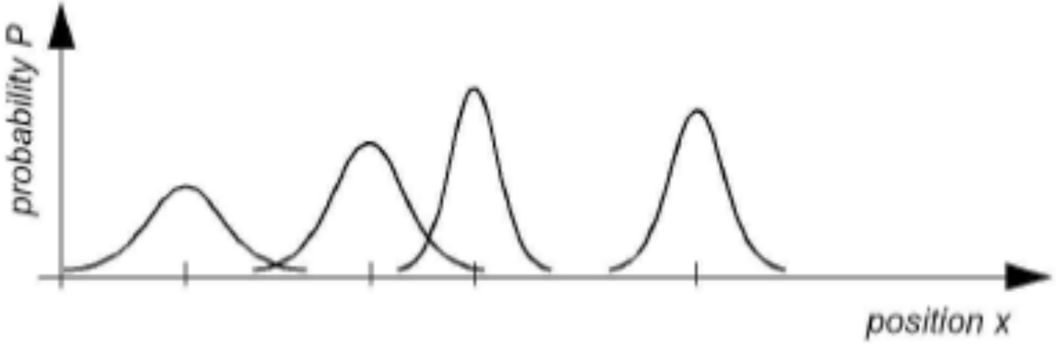


Belief Representation

- Continuous (single hypothesis)



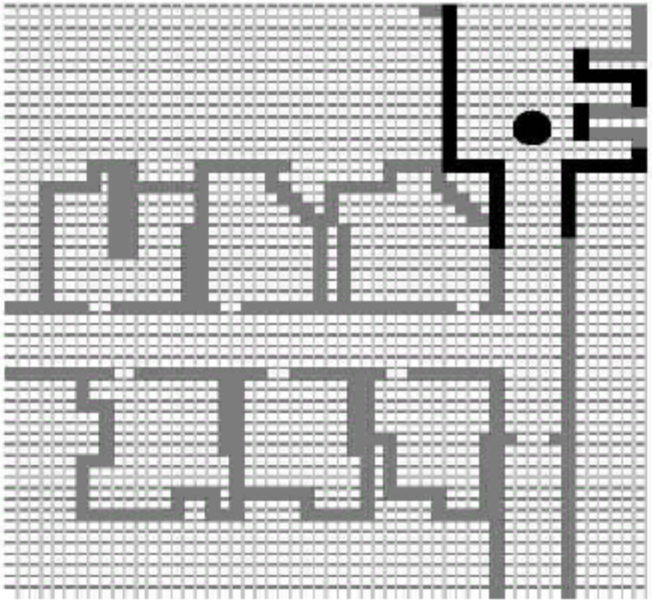
- Continuous (multiple hypothesis)



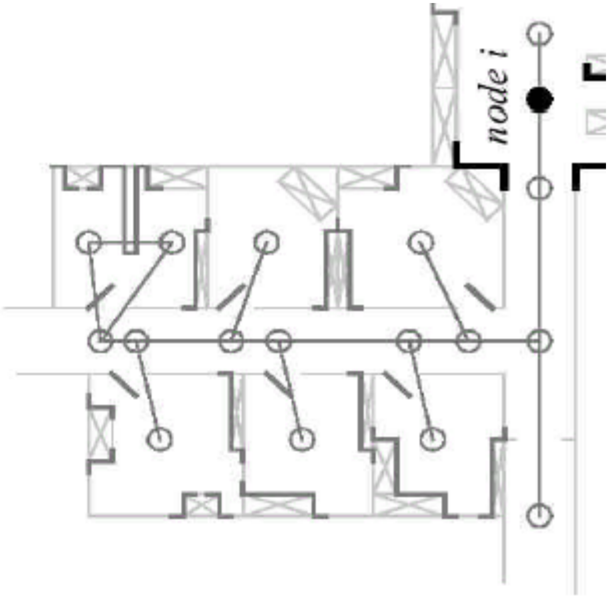
Belief Representation

- Or, we could assign a probability of being in some discrete locations:

Grid

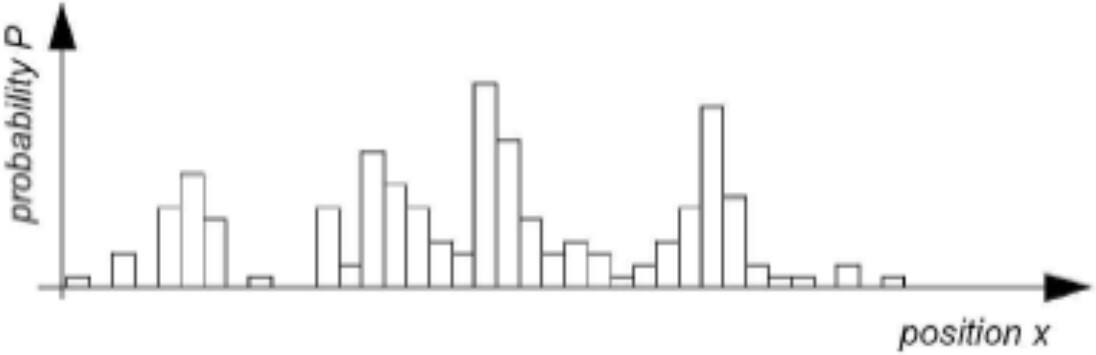


Topological



Belief Representation

- Discretized (prob. Distribution)



- Discretized Topological (prob. dist.)

Belief Representation

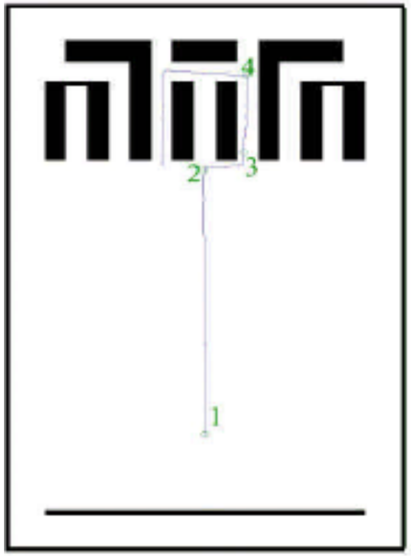
- Continuous
  - Precision bound by sensor data
  - Typically single hypothesis pose estimate
  - Lost when diverging (for single hypothesis)
  - Compact representation
  - Reasonable in processing power

Belief Representation

- Discrete
  - Precision bound by resolution of discretization
  - Typically multiple hypothesis pose estimate
  - Never lost (when diverges converges to another cell).
  - Memory and processing power needed (unless topological map used)
  - Aids discrete planner implementation

Belief Representation

- Multi-Hypothesis Example



Path of the robot

Belief states at positions 2, 3 and 4

Localization: Outline

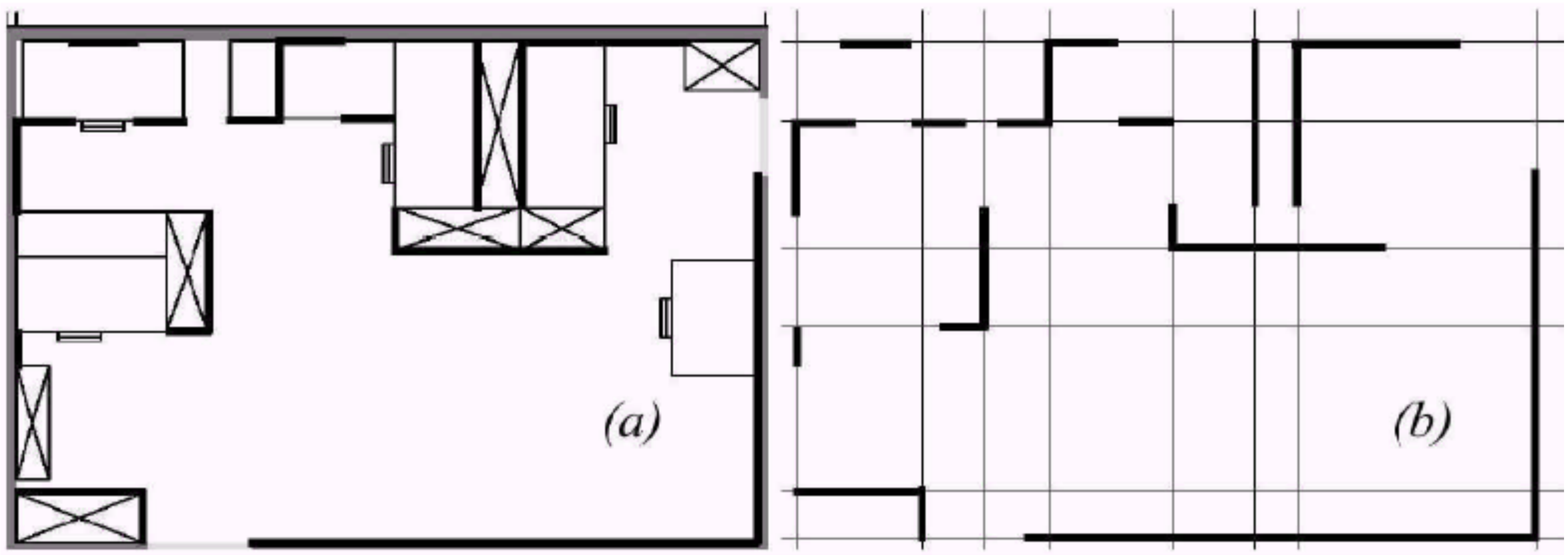
1. Localization Tools
    1. Belief representation
    2. Map representation
    3. Probability Theory
2. Overview of Algorithms

Map Representation

- The application determines Map precision
- The map and feature precisions must match the sensor precisions
- There is a clear trade-off between precision and computational complexity
- Similar to belief representations, there are two main types:
  - Continuous
  - Discretized

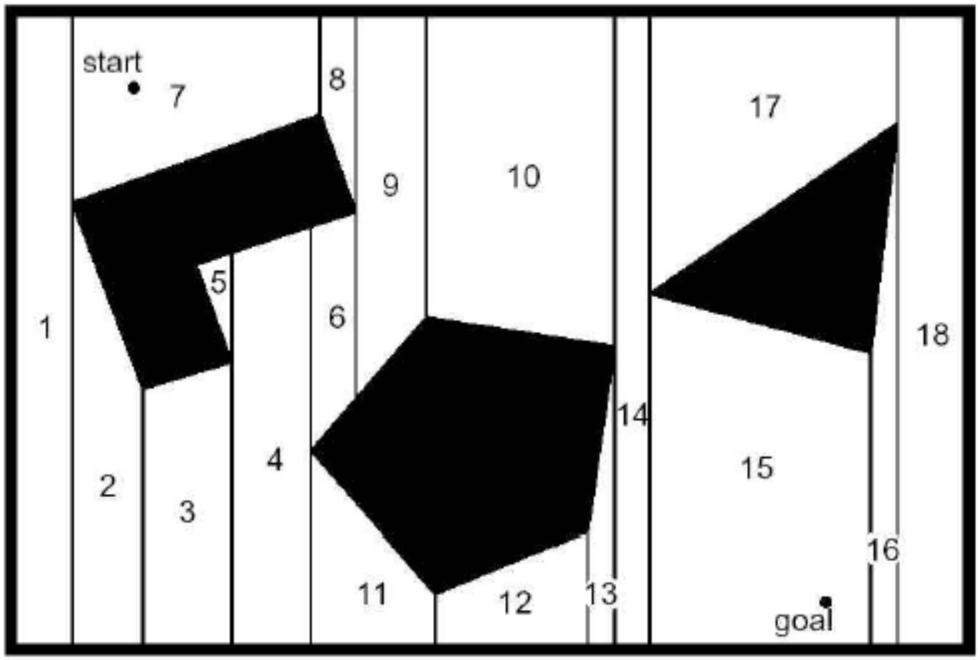
Map Representation

- Continous line-based



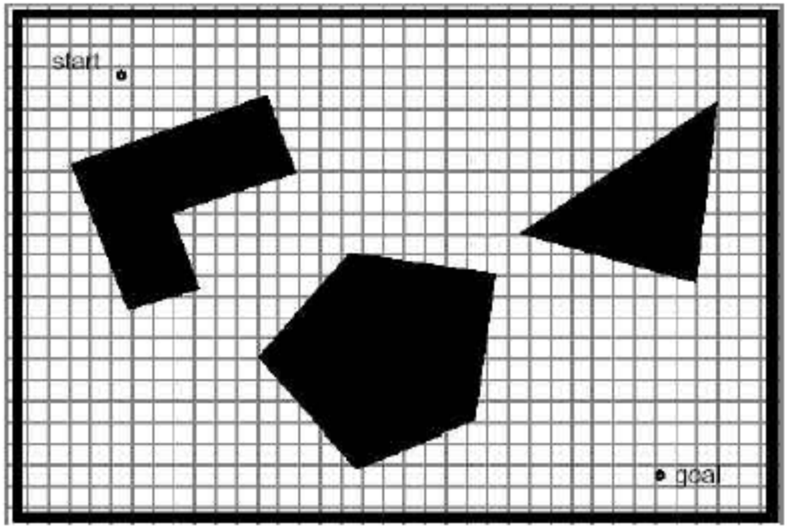
Map Representation

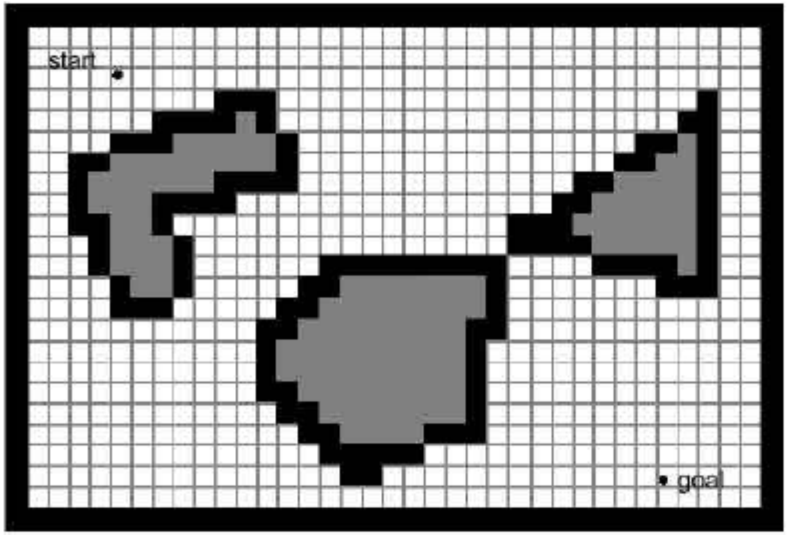
- Exact cell decomposition



Map Representation

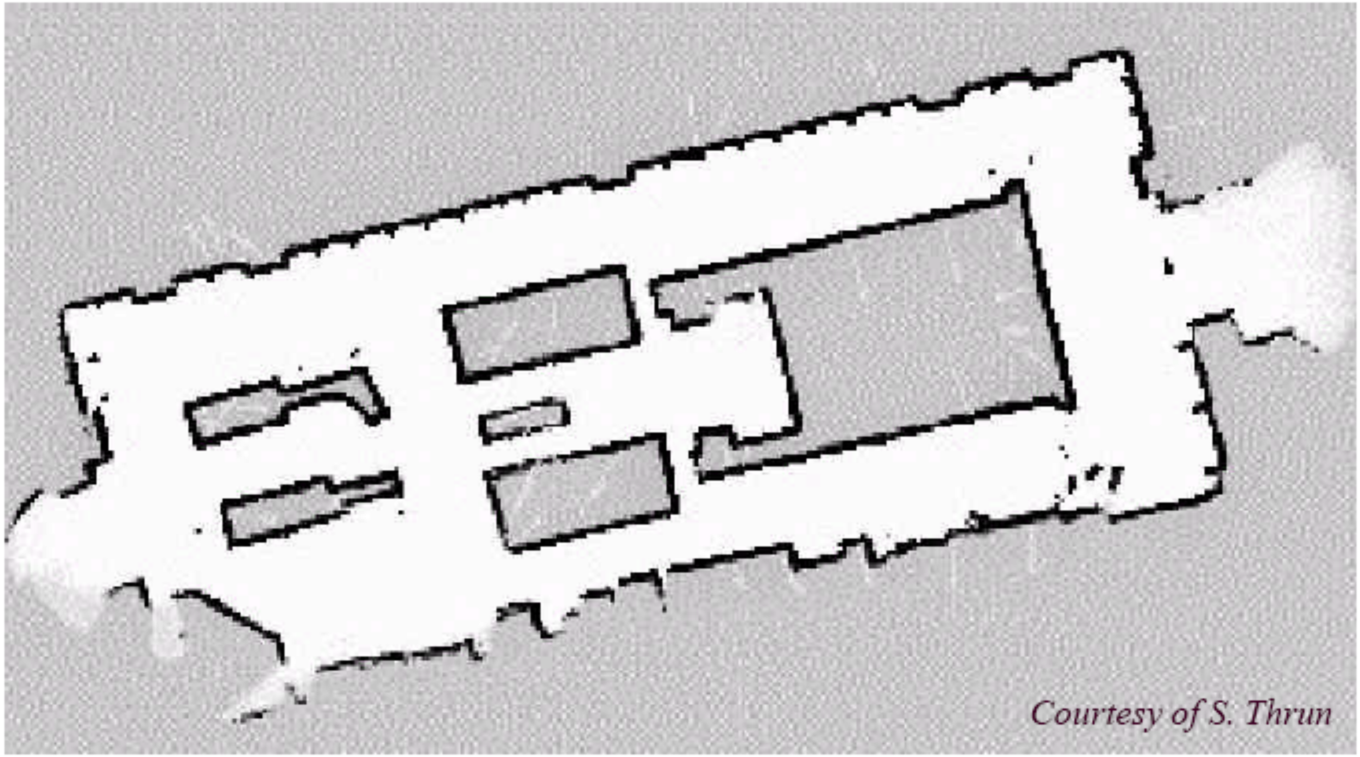
- Fixed cell decomposition





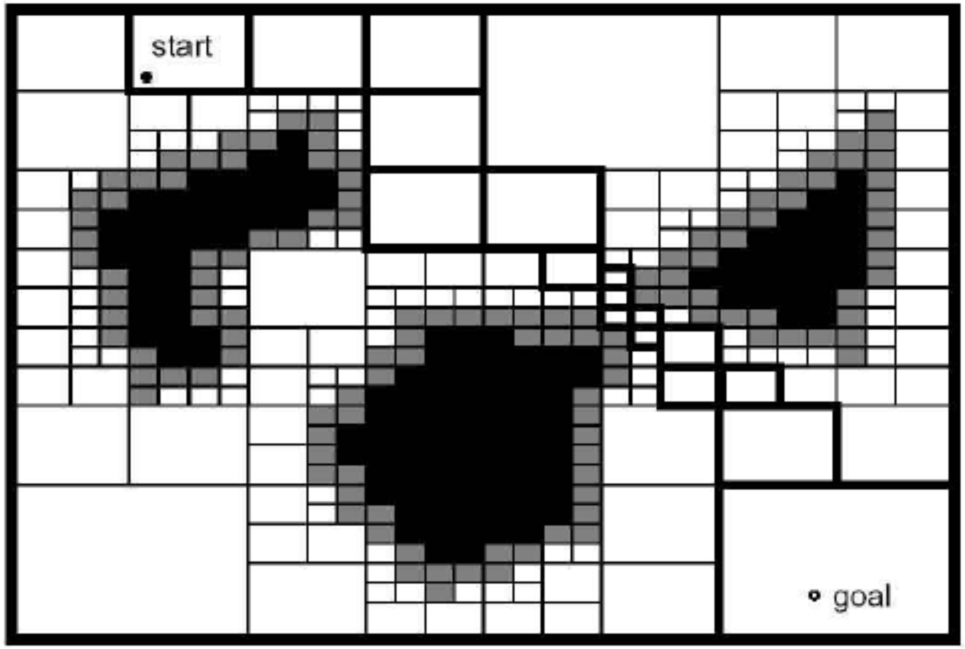
Map Representation

- Fixed cell decomposition



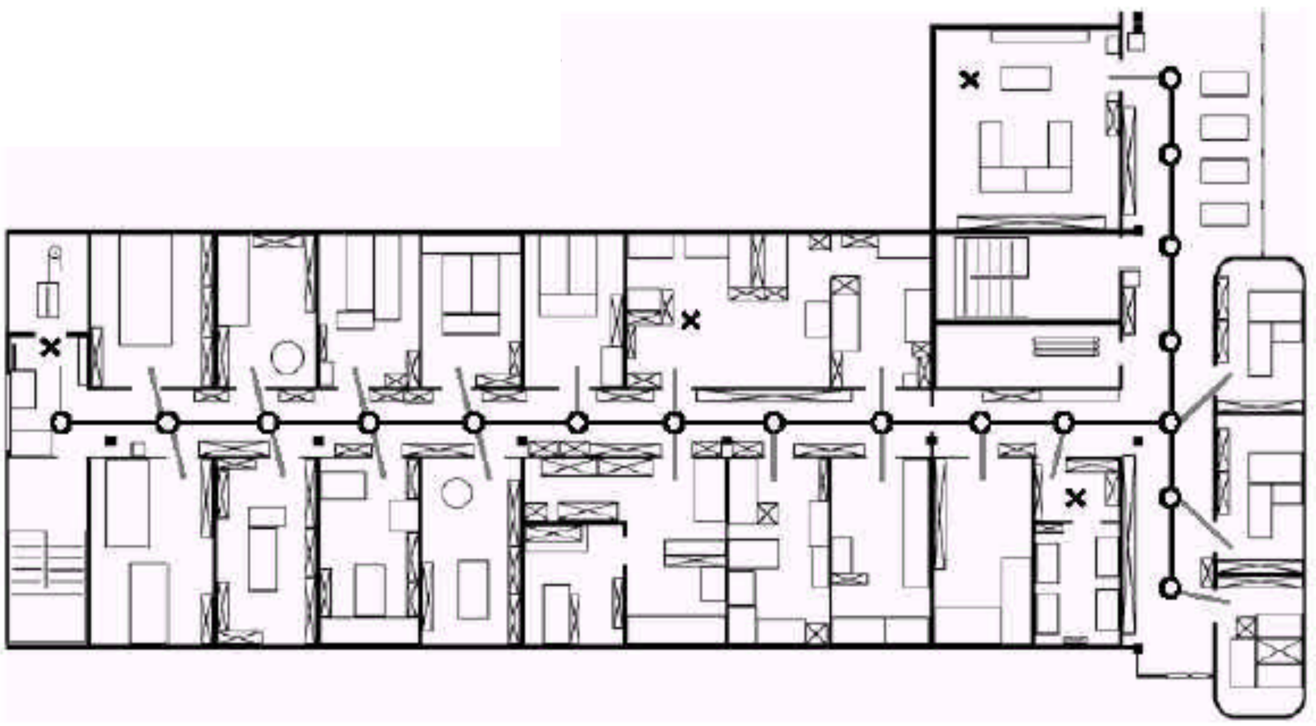
Map Representation

- Adaptive cell decomposition



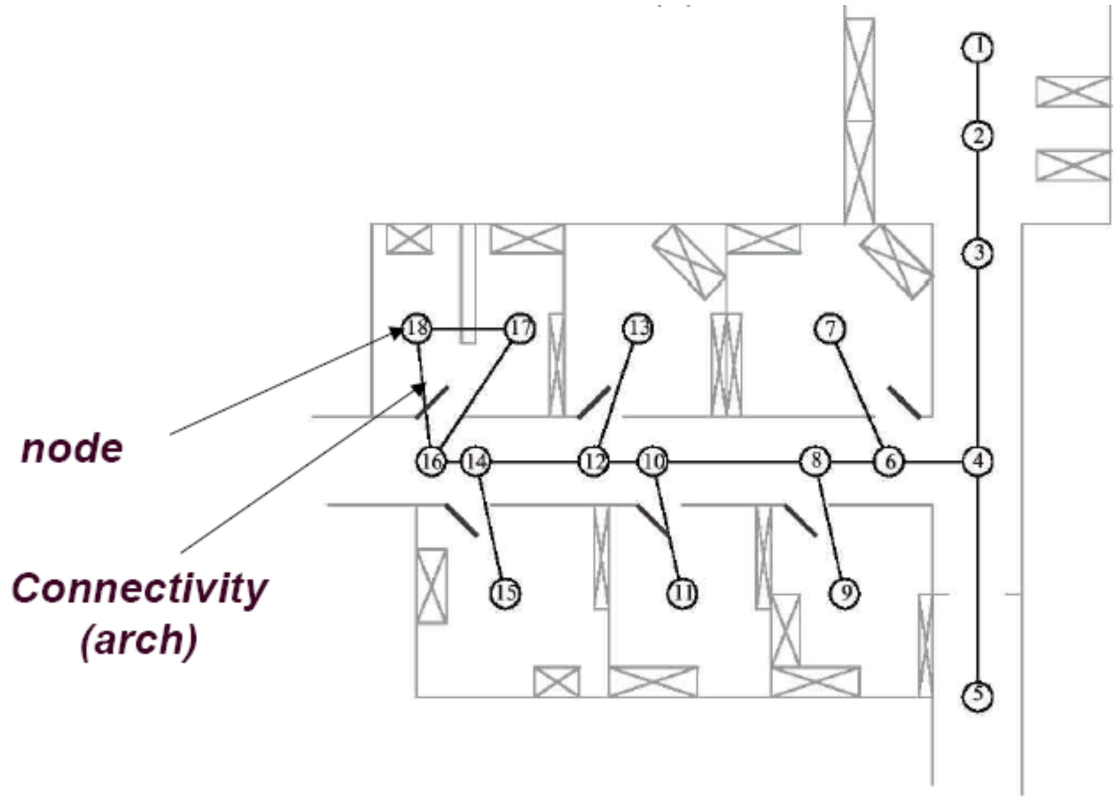
Map Representation

- Topological decomposition



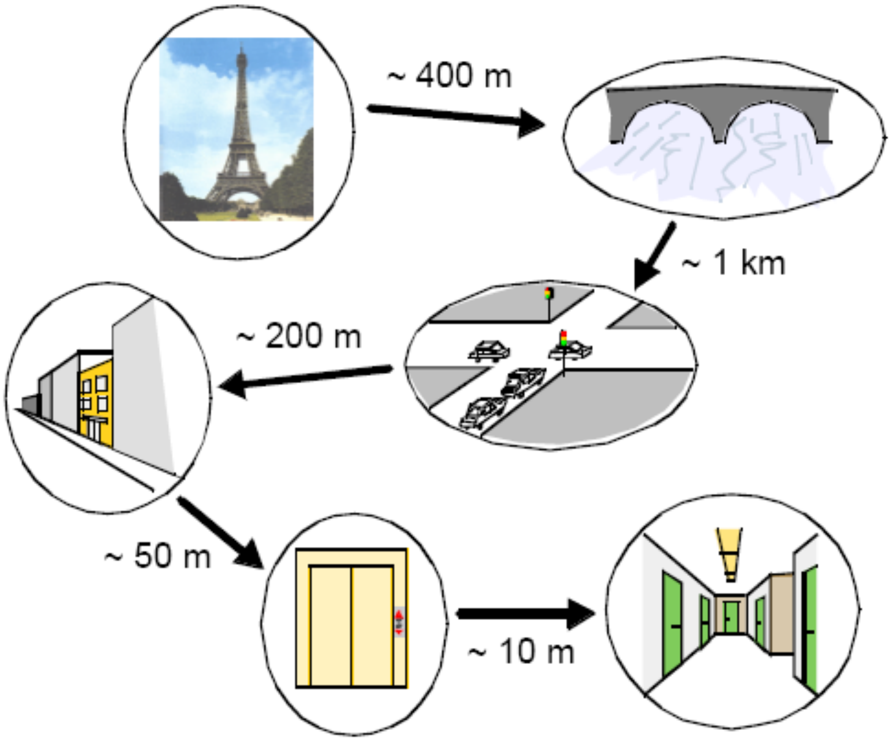
Map Representation

- Topological decomposition



Map Representation

- Topological decomposition



Localization: Outline

1. Localization Tools
    1. Belief representation
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    3. Probability Theory
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Basic Probability Theory

- Probability that A is true

$$P(A)$$

  - We compute the probability of each robot state given actions and measurements.
- Conditional Probability that A is true given that B is true

$$P(A \mid B)$$

  - For example, the probability that the robot is at position x_t given the sensor input z_t is $P(x_t \mid z_t)$

Basic Probability Theory

- Product Rule:

$$p(A \wedge B) = p(A \mid B)\, p(B)$$

$$p(A \wedge B) = p(B \mid A)\, p(A)$$

  - Can equate above expressions to derive Bayes rule.

- Bayes Rule:

$$p(A \mid B) = \frac{p(B \mid A)\, p(A)}{p(B)}$$

Localization: Outline

1. Localization Tools
2. Overview of Algorithms
    1. Typical Methods
    2. Basic Structure

Localization
Probabilistic Methods

- Problem Statement:
  - Determine the state of a robot in a known environment.
- Strategy:
  - It might start to move from a known location, and keep track of its position using odometry.
  - However, the more it moves the greater the uncertainty in its position.
  - Therefore, it will update its position estimate using observation of its environment

Localization
Probabilistic Methods

- Method:
  - Fuse the odometric position estimate with the observation estimate to get best possible update of actual position
  -
- This can be implemented with two main functions:

1. Act
2. See

Localization
Probabilistic Methods

- Action Update (Prediction)
  - Define function to predict position estimate based on previous state x_{t-1} and encoder measurement o_t or control inputs u_t

$$x'_t = Act\ (o_t\ ,\ x_{t-1})$$

  - Increases uncertainty

Localization
Probabilistic Methods

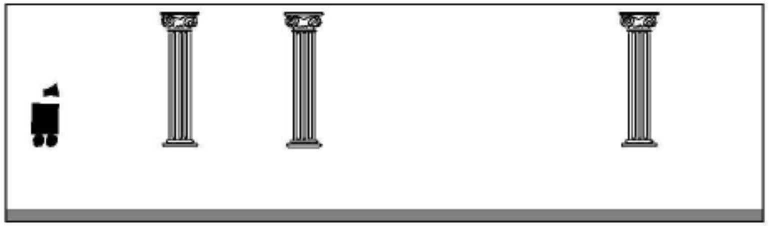
- Perception Update (Correction)
  - Define function to correct position estimate x'_t using exteroceptive sensor inputs z_t

$$x_t = See\ (z_t\ ,\ x'_t)$$

  - Decreases uncertainty

Localization
Probabilistic Methods

- Motion generally improves the position estimate.



Map-Based Localization Kalman Filtering vs. Markov

- Markov Localization
  - Can localize from any unknown position in map
  - Recovers from ambiguous situation
  - However, to update the probability of all positions within the whole state space requires discrete representation of space. This can require large amounts of memory and processing power.
- Kalman Filter Localization
  - Tracks the robot and is inherently precise and efficient
  - However, if uncertainty grows too large, the KF will fail and the robot will get lost.

Particle Filter Example