Unit 4: Localization Part 1
Maps, Beliefs, and Probability Review

Computer Science 4766/6912

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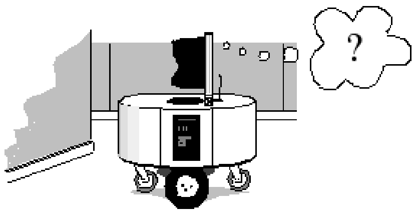
Navigation

- Providing robots with the requisite sensors, actuators, and algorithms to allow them to navigate in general environments is a big job; Four major subtasks are...
  - Perception: extract meaningful data from sensors
  - Localization: determine the robot's position
  - Cognition / Planning: decide on what actions to take
  - Motion control: control the actuators
- Localization answers the question "Where am I?"



Why is Localization Difficult?

Doesn't odometry solve the localization problem?

- Localization by odometry (i.e. integrating wheel rotation) is subject to cumulative error

Doesn't GPS solve the localization problem?

- GPS is enormously helpful in some applications, but has disadvantages for others:
  - GPS will be unavailable in a variety of situations:
    - Indoors
    - In obstructed areas
    - Underwater
    - In space (or on other worlds)
    - If the U.S. decides to make it unavailable
  - Insufficiently accurate for localizing smaller robots (such as the "body-navigating nanorobots of the future" [Siegwart and Nourbakhsh, 2004])

Issues

- Sensor noise:
  - Noise from proprioceptive sensors such as wheel encoders makes localization w.r.t. last known position difficult
  - Noise from exteroceptive sensors makes localization w.r.t. a map difficult
- **Perceptual aliasing**: the sensor data obtained at one location is indistinguishable from the data obtained at another location
- Noise introduced by movement:
  - Systematic errors: e.g. Differences between wheel radii
  - Non-Systematic errors: e.g. Wheel slippage

Map Representation

- **In this part of the course we will assume the existence of a map**
- Map used to compare with the robot's current sensory state
  - Can be supplied to the robot or,
  - Built autonomously — SLAM (Simultaneous Localization and Mapping)
- Choice of map representation depends on precision required, available sensors, and computational constraints

A **continuous representation** represents all mapped objects in continuous-space.

e.g. represent map as the set of infinite lines through object boundaries [Tomatis et al., 2003]

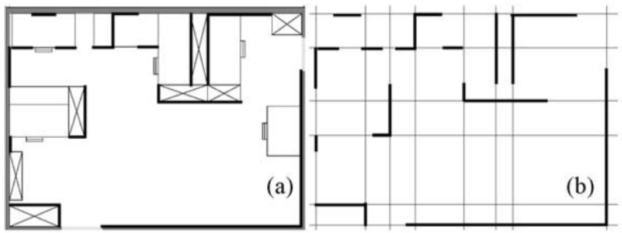
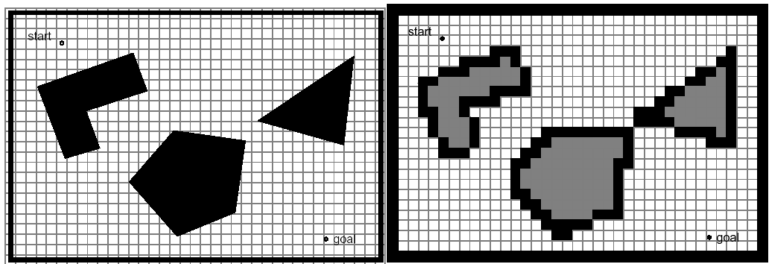


Fig. 4. An office of the institute (a) and the lines representing it in the local metric map (b). The black segments permit to see the correspondence between the two figures.

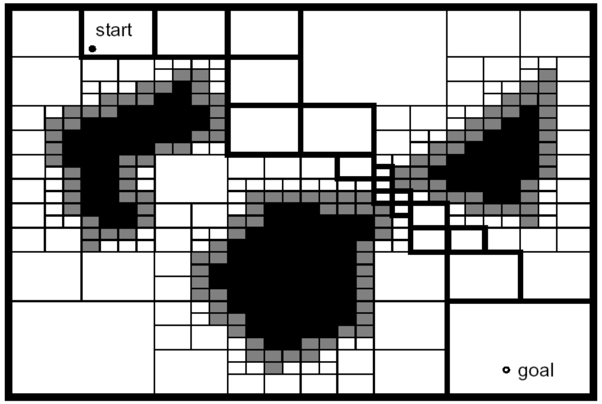
Cons: Requires storage proportional to the number of objects

An **occupancy grid** imposes a grid upon the world, with grid cells corresponding to free space left empty; and those for objects filled



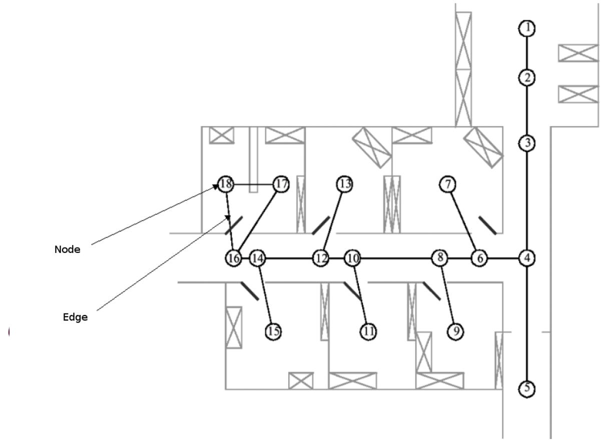
Cons: inexact, size of map grows quickly

An adaptive decomposition can improve the storage efficiency of an occupancy grid



Obtained by recursively splitting occupied grid cells into sub-cells

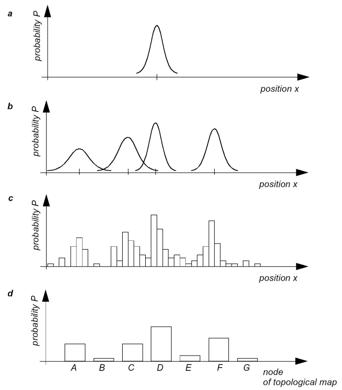
A **topological representation** represents the world as a graph, with *nodes* used to represent positions, and *edges* passable paths between positions



- Topological representations have two main requirements:
  1. A method to detect current position (node)
  2. A method of travelling between nodes (e.g. beacon aiming, corridor centreing, wall following, visual homing,...)
- Visual features particularly useful for (1)
- pros:
  - The *local navigation strategies* required for (2) can be quite simple
  - This representation is lightweight (low memory cost) and well-suited for planning
- cons:
  - Difficulty in maintaining a consistent density of nodes
  - Subject to perceptual aliasing problems

Belief Representation

- We will represent a robot's belief in its position as a probability distribution
- There are a number of ways to represent probability distributions
  - Continuous or discrete
  - Single-hypothesis or multiple-hypothesis
    - Single-hypothesis: The robot believes it is at one position with some margin for error
    - Multiple-hypothesis: The robot can represent the belief that it could be at a number of possible positions



(a) Continuous, single-hypothesis (Gaussian)

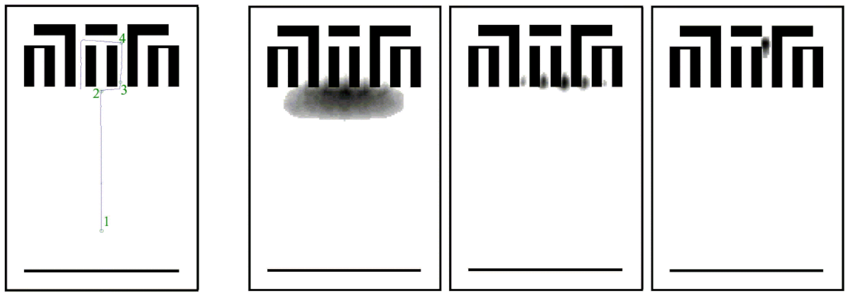
(b) Continuous, multiple-hypothesis (mixture of Gaussians)

(c) Discrete, multiple-hypothesis

(d) Discrete, multiple-hypothesis (for a topological map)

- Single-hypothesis belief:
  - (a) in previous slide
  - Very efficient to update
  - May not be suitable if starting from a position of global uncertainty (i.e. no clue as to where you are)
- Multiple-hypothesis beliefs:
  - (b), (c), or (d) on previous slide
  - A sampled representation of a continuous distribution is also possible (Monte Carlo Localization)
  - Representation is more powerful, but updates can be very expensive

Example of multiple-hypothesis belief tracking using a discrete representation,



Path of the robot *Belief states at positions 2, 3 and 4*

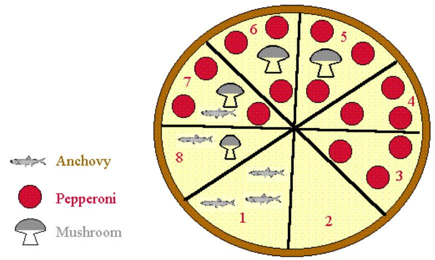
Large initial uncertainty is reduced by new observations

Probability Review

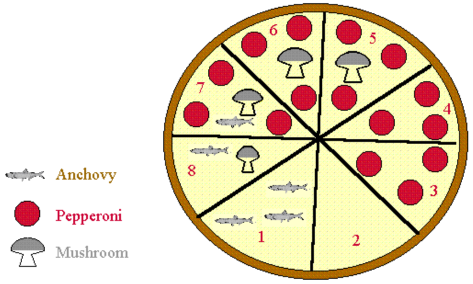
To understand probabilistic localization we will have to review some concepts from probability. We start with **conditional probability**.

Given that some event B has occurred, the probability $p(A|B)$ gives the conditional probability that A has also occurred.

To illustrate, consider the following probability pizza:



Assume that we pick a random slice of pizza with uniform probability...



$p(Pepperoni) = 5/8$

$p(Anchovies) = 3/8$

$p(Anchovies|Pepperoni) = 1/5$

The definition of conditional probability:

$$p(A|B) = \frac{p(A \wedge B)}{p(B)}$$

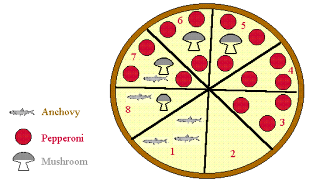
Bayes Rule

If we write the definition of conditional probability as $p(B|A)$ we can obtain the following well-known rule (DERIVATION COVERED ON BOARD),

$$p(A|B) = \frac{p(B|A)p(A)}{p(B)}$$

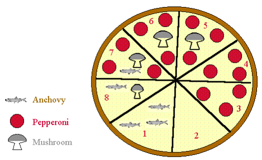
This is called Bayes rule and allows us to calculate a conditional probability (a.k.a. prior probability) from its “inverse”

e.g. What is $p(Pepperoni|Anchovies)$?



$$p(Pe|An) = \frac{p(An|Pe)p(Pe)}{p(An)} = \frac{1}{3}$$

Theorem of Total Probability



$p(Mushrooms) = p(Mu) = 1/2$

If $A_1, \ldots, A_n$ are mutually exclusive and exhaustive events, the theorem of total probability says that:

$$p(B) = \sum_{i=1}^{n} P(B|A_i)P(A_i)$$

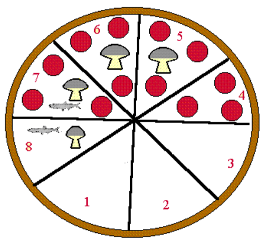
$$\begin{aligned} p(Mu) &= p(Mu|Slice1)p(Slice1) + p(Mu|Slice2)p(Slice2) + \cdots \\ &= 0 \cdot 1/8 + 0 \cdot 1/8 + 0 \cdot 1/8 + 0 \cdot 1/8 + \\ &\quad 1 \cdot 1/8 + 1 \cdot 1/8 + 1 \cdot 1/8 + 1 \cdot 1/8 = 1/2 \end{aligned}$$

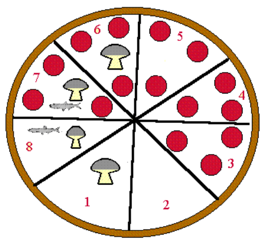
Independence

Two events A and B are independent **iff** their joint probability is equal to the product of their individual probabilities

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

For the pizza on the left, events Pe and An are independent: COVERED ON BOARD





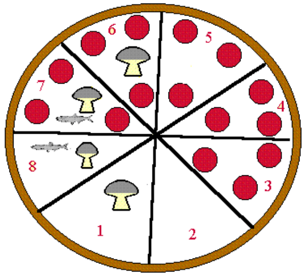
However, for the pizza on the right these events are **not** independent: COVERED ON BOARD

Conditional Independence

Sometimes two events can be independent, but only if some other event is known to have occurred. This is known as **conditional independence** and is expressed by the following relation,

$$p(A \wedge B|C) = p(A|C)p(B|C)$$

For this pizza, if we know that a slice contains mushrooms, the event that it contains anchovies is independent from the event that it contains pepperoni,



References

Siegwart, R. and Nourbakhsh, I. (2004).
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Tomatis, N., Nourbakhsh, I., and Siegwart, R. (2003).
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