Robotics

Chapter 25

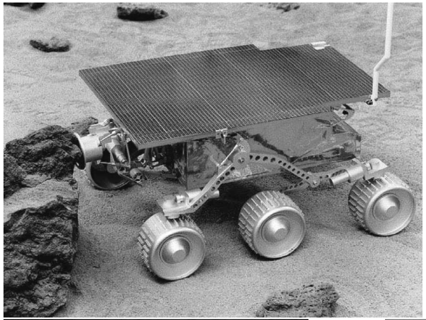
Outline

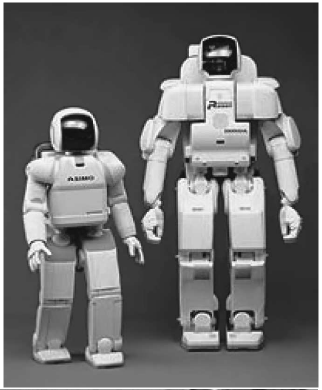
Robots, Effectors, and Sensors

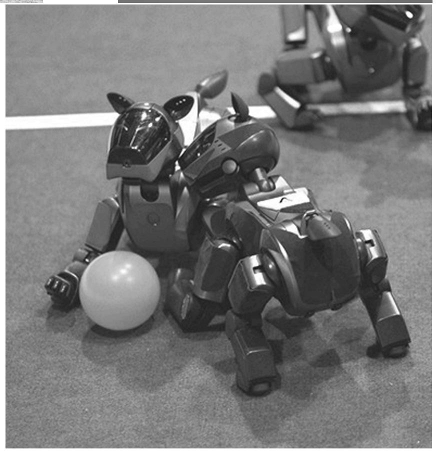
Localization and Mapping

Motion Planning

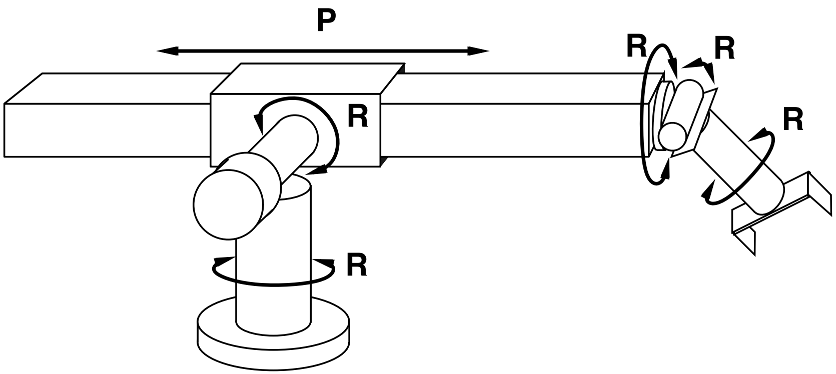
Mobile Robots







Manipulators

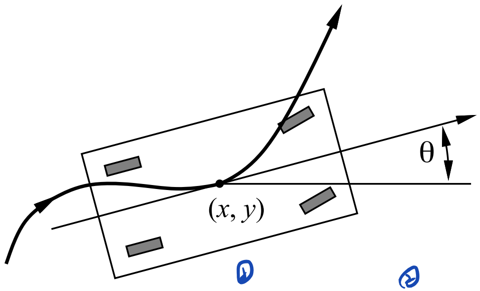


Configuration of robot specified by 6 numbers

$\Rightarrow$ 6 degrees of freedom (DOF)

6 is the minimum number required to position end-effector arbitrarily.
For dynamical systems, add velocity for each DOF.

Non-holonomic robots



x, y, θ ① accelerate/break ② adjust the wheel

A car has more DOF (3) than controls (2), so is non-holonomic;
cannot generally transition between two infinitesimally close configurations

Sources of uncertainty in interaction

There are two major sources of uncertainty for any interacting mobile agent (human or robotics):

◊ Everything they perceive (percepts)

◊ Everything they do (actions)

We do not see the world as it is

Kant (1724-1804)

♢ Distinction between 'things-in-themselves', and 'appearances'.

♢ We have sensory states, but how do we know how (even if) these relate to the world?

We do not see the world as it is

◇ What do you really see?

- Small foveal region in colour.
- Most of field of view is monochrome, at low resolution, and sensitive to motion.
- 2D image only (binocular seldom used in practice).

◇ Occasionally, perceived reality breaks down:

- hallucinations
- optical illusions

Uncertainty in actions

♢ Consider an agent action sequence as discussed in AIMA

- Move forward 1 metre;
- Turn right (90 degrees);
- Move forward 2 metres;
- Turn left;
- Turn left;
- Move forward 2 metres.
- Turn left;
- Move forward 1 metre.

♢ Go into an open space, close your eyes (no sensory feedback - that would be cheating!), and attempt this sequence.

♢ How close do you get?

Sources of uncertainty in motion actions

- slippage;
- inaccurate joint encoding;
- rough surfaces;
- obstacles;
- effector breakdown (injuries);
- ....

◇ All these errors accumulate without bound.

◇ Thus, starting out with perfect knowledge, and moving using actions with very small error, after an infinitely long action sequence a system will have infinite error in its position estimate.

Dealing with uncertainty in motion actions

◊ Use sensors to verify actions (not simple).

Sources of uncertainty robotic perception

◇ Let's take a very simple sensor - distance sensor (laser range finder).

◇ Returns a number corresponding to nearest obstacle in a straight-line path, up to some finite distance.

◇ Has some known error (non-precise location).

◇ Has some known false positive/false negative rates (whether an obstacle is there or not).

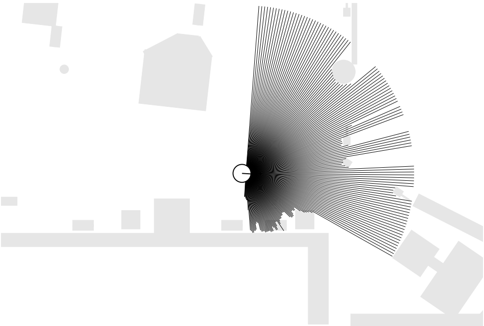
◇ Has small spatial extent - what if partially obstructed?

◇ Finite time means cannot check every location, what does a reading say about the readings are neighbouring points.

Sensors

Range finders: sonar (land, underwater), laser range finder, radar (aircraft), tactile sensors, GPS

physical pressure sensors



Imaging sensors: cameras (visual, infrared)

Proprioceptive sensors: shaft decoders (joints, wheels), inertial sensors, force sensors, torque sensors

phone

Implications of sensor uncertainty

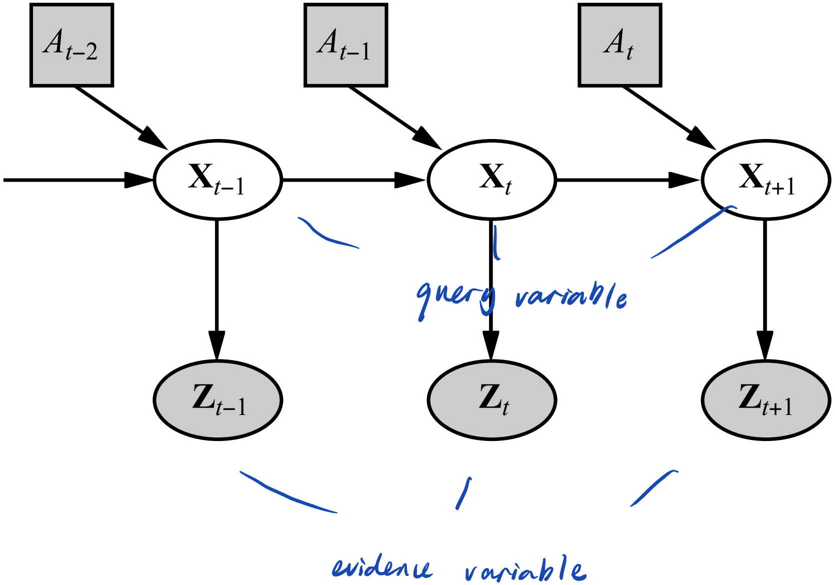
♢ Must make assumptions about the way the world behaves in order to interpret the readings at all. For example:

- Some finite resolution sampling is sufficient to detect obstacles (consider an obstacle that consists of hundreds of long pins, sparsely distributed, pointing towards the sensor).
- Must know something about the structure of the robot to decide what an obstacle is.
- Given some sensor reading, only have a finite probability that it is correct - must have some way of dealing with this.

Localization—Where Am I?

An action A_t at time t results in
state X_{t+1} and observation Z_{t+1}

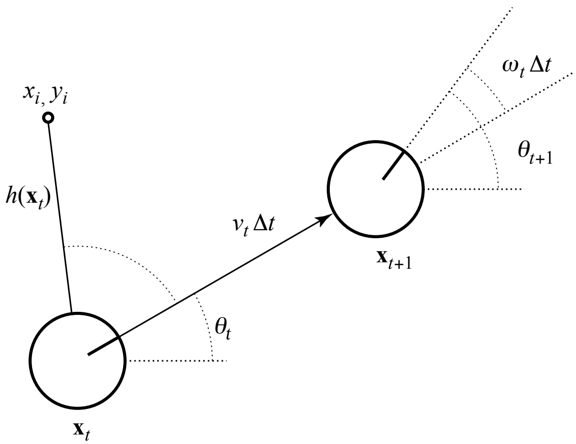
Compute current location and orientation (pose) given observations:

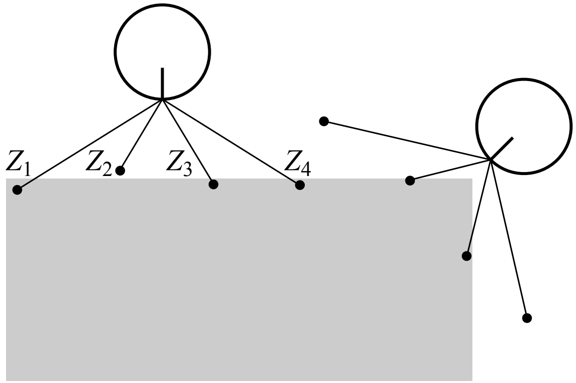


Localization contd.

Sensor Model: Use observation $h(x_t)$ of landmark x_i, y_i
to estimate state x_t of robot.

Motion Model: Update state using its movements $v_t\Delta t$ and $\omega_t\Delta t$





Assume Gaussian noise in motion prediction, sensor range measurements

Localization contd.

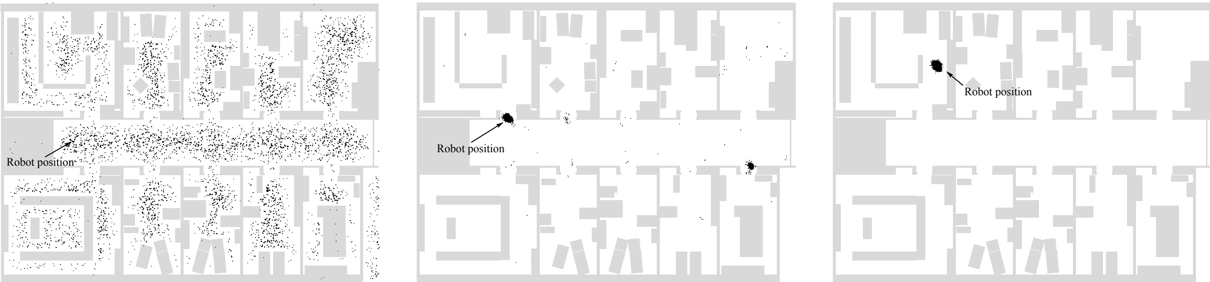
Can use **particle filtering** to produce approximate position estimate

1) Start with random samples from uniform prior distribution for robot position.

2) Update likelihood of each sample using sensor measurements.

3) Resample according to updated likelihoods.

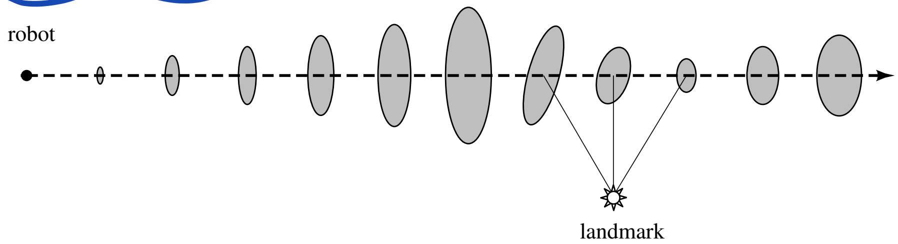
delete low likelihood



Localization contd.

We need to continuously update our distribution for the current state
using the latest measurements.

Uncertainty of the robot's state grows as it moves
until we find a landmark.



Assumes that landmarks are *identifiable*—otherwise, posterior is multimodal

Mapping

Localization: given map and observed landmarks, update pose distribution

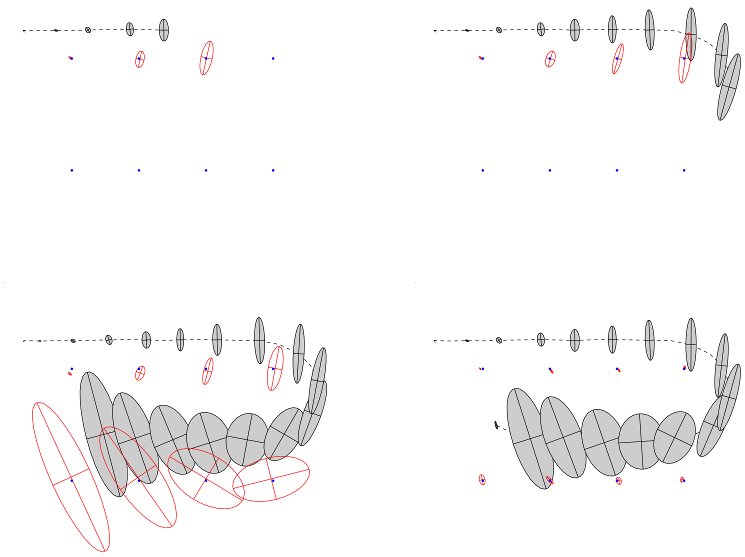
Mapping: given pose and observed landmarks, update map distribution

Simultaneous Localization and Mapping (SLAM):
given observed landmarks, update pose and map distribution

Probabilistic formulation of SLAM:
add landmark locations $L_1, \ldots, L_k$ to the state vector,
proceed as for localization

Mapping contd.

Consider space with 8 identical landmarks:

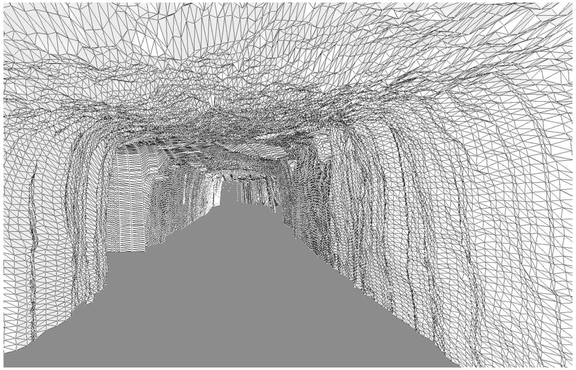


When first landmark detected again:

no uncertainty about robot or landmark positions

3D Mapping example

Mapping a coal mine:



Bayesian Inference on Sensors

Need some way to determine whether an obstacle is there, given multiple measurements from a sensor.

What is Bayesian inference? (revision)

there is an obstacle

- A method for determining the *probability* that a hypothesis is true, given a set of measurements.
- Probability $\approx$ belief.

Elements of Conditional Probability: revision

The probability that A is true, *given* the condition B:

$$P(A \mid B) \tag{1}$$

Examples:

- $P(\text{I will get hit by a car tomorrow}) = 0.0001$
- $P(\text{I will get hit by a car tomorrow} \mid \text{I ride to Frankston}) = 0.01$
- $P(\text{I will get hit by a car tomorrow} \mid \text{I stay home all day}) = 0.0000001$

Bayes Law: revision

Bayes Law asks:

- Given measurement M;
- What is the probability of hypothesis H?

Bayes Law:

$$P(H \mid M) = \frac{P(M \mid H)}{P(M)} P(H) \tag{2}$$

Bayes Law: revision

Bayes Law:

$$P(H \mid M) = \frac{P(M \mid H)}{P(M)} P(H) \tag{3}$$

Elements:

- $P(H \mid M)$: posterior probability of H.
- $P(H)$: prior probability of H.
- $P(M \mid H)$: sensor model. ⇒ prob that get recording given that there is an obstacle
- $P(M)$: normalisation factor.

Normalisation:

summing over whether hypothesis is T / F

$$P(M) = P(M \mid H)P(H) + P(M \mid \neg H)P(\neg H) \tag{4}$$

Example

Obstacle detection:

- The odds of there being an obstacle present are 1 in 10.

  assume obstacle, actually no   assume no obstacle, actually yes
- The detector has 5% false positive rate and 10% false negative rate.

  P(positive | noobstacle)   P(negative | obstacle).
- Probability that an obstacle is present if the det ector returns positive?
- Probability that an obstacle is present if the det ector returns negative?

Priors:

$$P(\text{obstacle}) = 0.1$$
$$P(\text{noobstacle}) = 0.9 \quad (5)$$

$$P(\text{obstacle} \mid \text{positive}) = \frac{P(\text{positive} \mid \text{obstacle}) \times P(\text{obstacle})}{P(\text{positive})} = \frac{0.9 \times 0.1}{0.9 \times 0.1 + 0.9 \times 0.05} = 0.667$$

$$P(\text{obstacle} \mid \text{negative}) = \frac{P(- \mid o) \cdot P(o)}{P(- \mid o) \cdot P(o) + P(- \mid n) \cdot P(n)} = \frac{0.1 \times 0.1}{0.1 \times 0.1 + 0.9 \times 0.95} = 0.0116$$

Example continued

Sensor model:

$$
\begin{aligned}
P(\text{positive} \mid \text{obstacle}) &= 0.9 \\
P(\text{negative} \mid \text{obstacle}) &= 0.1 \\
P(\text{negative} \mid \text{notobstacle}) &= 0.95 \\
P(\text{positive} \mid \text{notobstacle}) &= 0.05
\end{aligned}
\tag{6}
$$

If the sensor returns positive:

$$
P(\text{obstacle} \mid \text{positive}) = \frac{0.9}{0.9 \times 0.1 + 0.05 \times 0.9} 0.1 = 0.667 \tag{7}
$$

If the sensor returns negative:

$$
P(\text{obstacle} \mid \text{negative}) = \frac{0.1}{0.1 \times 0.1 + 0.95 \times 0.9} 0.1 = 0.0116 \tag{8}
$$

why independent is important?

Incremental form of Bayes Law

more independent measurement (even if it is noise), the better our estimate

Bayes Law can be extended to handle multiple measurements.

- Given a set of *independent* measurements $\{M_j\}$;
- What is the probability of the hypothesis H?

If measurements are independent, can use incremental form.

- Given the *current* probability distribution $P(H)$;
- And a *new* measurement M
- What is the updated probability distribution $P(H)$?

Use Bayes Law in incremental form:

$$P(H) \xleftarrow{M} \underbrace{\frac{P(M \mid H)}{P(M)}P(H)}_{P(H|M)} \quad (9)$$

Sometimes called Bayesian *update* rule.

$$P(H|M) = \frac{P(M|H)\cdot P(H)}{P(M)}$$

$$P(H|M_1,M_2) = \frac{P(M_1,M_2|H)\cdot P(H)}{P(M_1,M_2)}$$

$$= \frac{P(M_1,M_2|H)\cdot P(H)}{P(M_1,M_2|H)\cdot P(H) + P(M_1 M_2|\neg H)\cdot P(\neg H)}$$

measurements independence

$$= \frac{P(M_1|H)\cdot P(M_2|H)\cdot P(H)}{P(M_1|H)\cdot P(M_2|H)\cdot P(H) + P(M_1|\neg H)\cdot P(M_2|\neg H)\cdot P(\neg H)}$$

normalize by $P(M_1)$

$$= \frac{P(M_1|H)\cdot P(M_2|H)\cdot P(H)/P(M_1)}{[P(M_1|H)\cdot P(M_2|H)\cdot P(H)/P(M_1)] + [P(M_1|\neg H)\cdot P(M_2|\neg H)\cdot P(\neg H)/P(M_1)]}$$

$$= \frac{P(M_2|H)\cdot P(H|M_1)}{P(M_2|H)\cdot P(H|M_1) + P(M_2|\neg H)\cdot P(\neg H|M_1)}$$

Example

Obstacle detection (again):

- The odds of there being an obstacle present are 1 in 10.
- The detector has 5% false positive rate and 10% false negative rate.

$P(+|N) = 0.05$ $\quad$ $P(-|O) = 0.1$

- What is the probability that an obstacle is present if the detector returns:
  - One positive?
  - Two positives?
  - Two positives and a negative?

$$P(H|++-) \overset{?}{=} P(H|+-+)$$

1st positive

$$P(O|+) = \frac{P(+|O)\cdot P(O)}{P(+|O)\cdot P(O) + P(+|N)\cdot P(N)} = \frac{0.9 \times 0.1}{0.9\times 0.1 + 0.05 \times 0.9} = 0.67$$

2nd positive

updated prior

$$P(O|+,+) = \frac{P(+|O)\cdot P(O|+)}{P(+|O)\cdot P(O|+) + P(+|\neg O)\cdot P(\neg O|+)}$$

$$= \frac{0.9 \times 0.67}{0.9 \times 0.67 + 0.05 \times 0.33} = 0.97$$

Example

Time series:

Time	M	$P(\text{obs})$	$P(\text{noobs})$
0	-	0.10	0.90
1	positive	0.67	0.33
2	positive	0.97	0.03
3	negative	0.79	0.21

Motion Planning

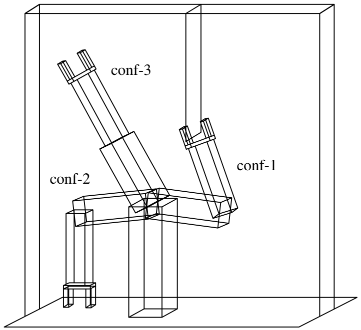
Now we know:

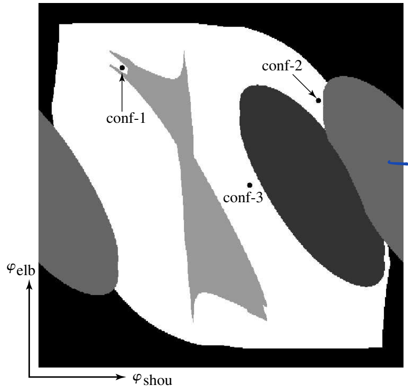
- where we are
- where the obstacles are
- where we want to go

Next challenge – How do we get there?

Motion Planning

Idea: plan in configuration space defined by the robot's DOFs





→ impossible

Solution is a point trajectory in free C-space

Configuration space planning

Basic problem: ∞^d states! Convert to **finite** state space.

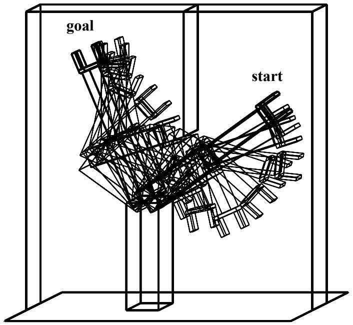
Cell decomposition:

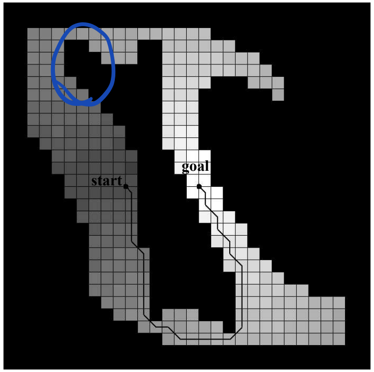
divide up space into simple cells,
each of which can be traversed "easily" (e.g., convex)

Skeletonization:

identify finite number of easily connected points/lines
that form a graph such that any two points are connected
by a path on the graph

Cell decomposition example





may

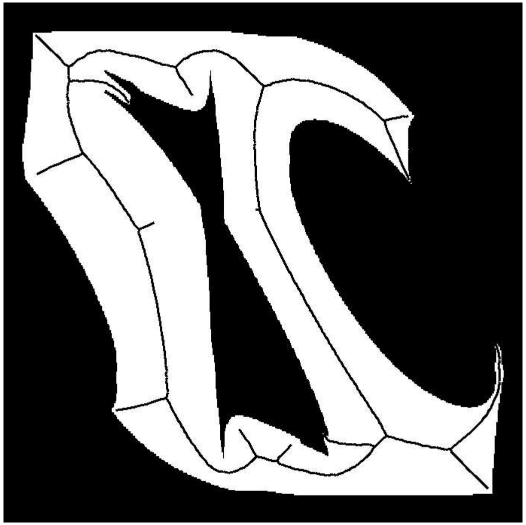
Problem: may be no path in pure freespace cells ⇒ lose some details

Solution: recursive decomposition of mixed (free+obstacle) cells

Skeletonization: Voronoi diagram

Voronoi diagram: locus of points equidistant from obstacles

equal distance from obstacles

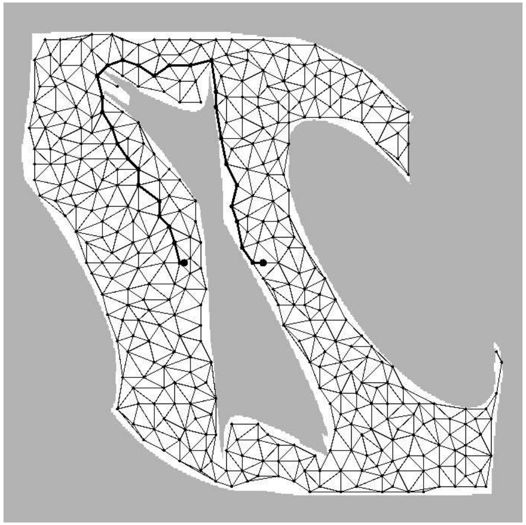


Problem: doesn't scale well to higher dimensions

Skeletonization: Probabilistic Roadmap

A probabilistic roadmap is generated by generating random points in C-space and keeping those in freespace; create graph by joining pairs by straight lines

turn to graph search



Problem: need to generate enough points to ensure that every start/goal pair is connected through the graph

Summary

♢ Percepts and actions are both subject to uncertainty.

♢ We cannot interpret our percepts without having a model of what they mean, and without (partially invalid) assumptions about how they perform.

♢ Uncertainty in robot perception.

♢ Incremental form of Bayes Law.

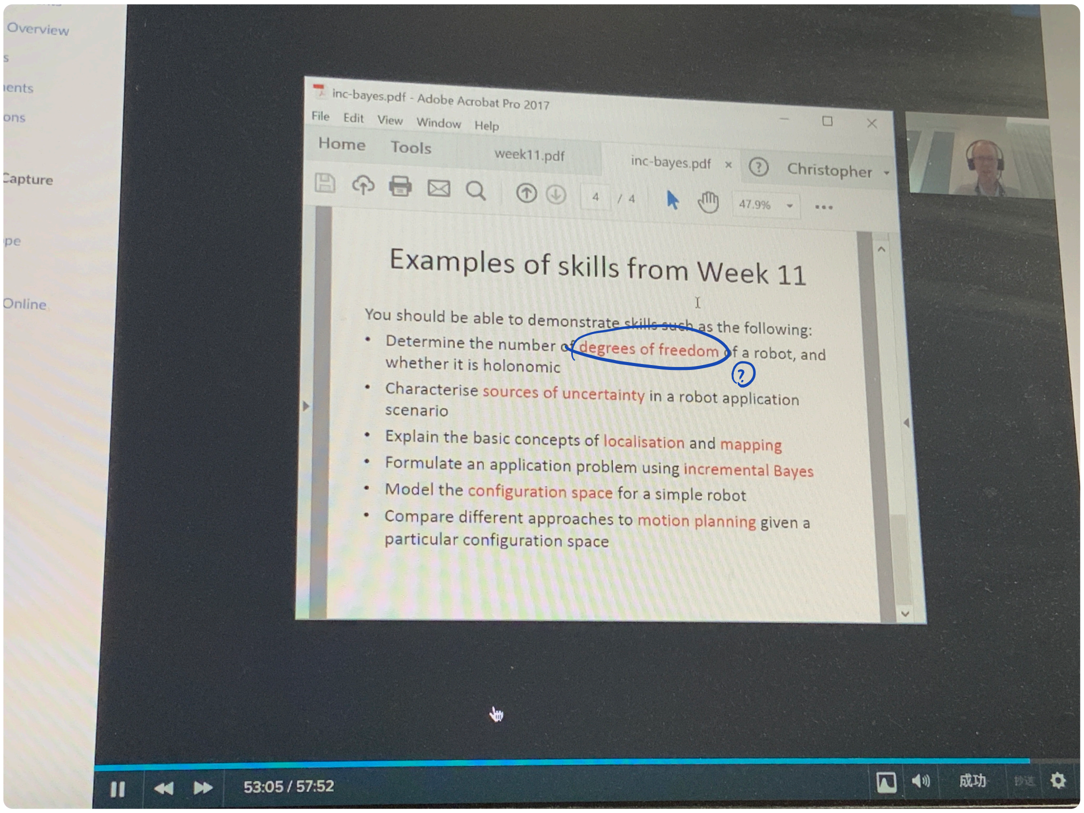
♢ Motion planning.

Implications for AI

If you can't rely on your perceptions or your actions, does that mean that Agent methods we have discussed are of no use?

- Many problems don't have uncertainty for perceptions and actions, e.g., scheduling, planning, game-playing, text-based machine translation.
- Can incorporate standard agent methods within a system that handles uncertainty, i.e., re-plan if something goes wrong.
- Can apply uncertainty handlers to whole system - e.g., Bayesian inference.

Certainly for autonomous robots and computer vision interaction with an environment creates many problems that cannot be easily handled with conventional AI techniques.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Examples of skills from Week 11
You should be able to demonstrate skills such as the following:
• Determine the number of degrees of freedom of a robot, and whether it is holonomic
?
• Characterise sources of uncertainty in a robot application scenario
• Explain the basic concepts of localisation and mapping
• Formulate an application problem using incremental Bayes
• Model the configuration space for a simple robot
• Compare different approaches to motion planning given a particular configuration space
53:05 / 57:52