History and Current Challenges in the field of Robotics

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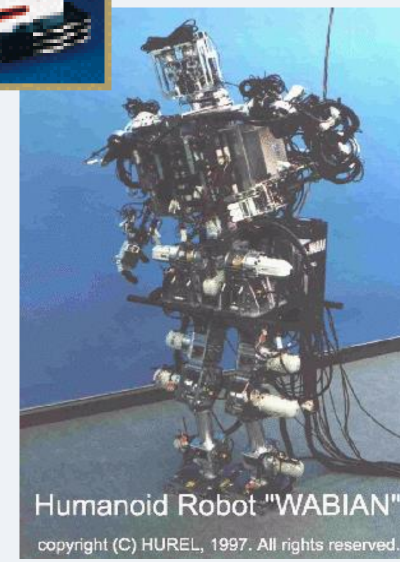
Outline

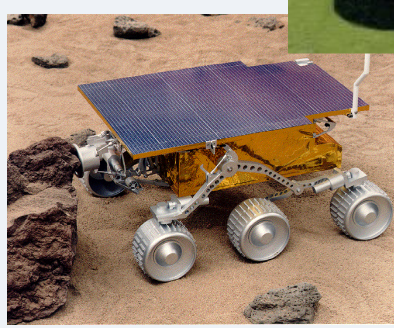
- Definition of a robot
- History of robotics
- Sub-field in Robotics

Defining “robot”

- What makes a robot
- Sensors, sensor space
- State, state space
- Action/behavior, effectors, action space
- The spectrum of control

Robots Today





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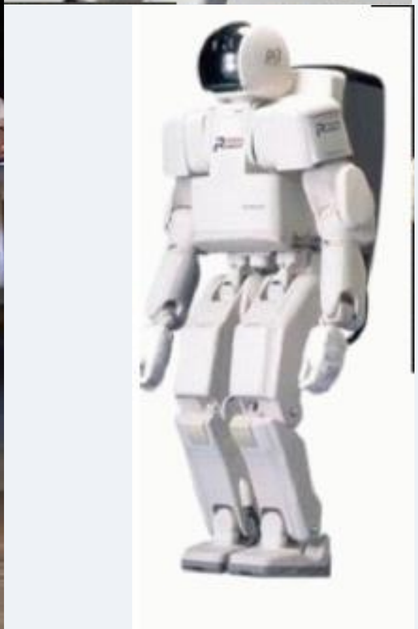
Robots Today: Anthropomorphic



Robots today: Animal-like robots

Why "robot"?

- The term "robot" comes from Karel Capek's 1921 play RUR (Rossum's Universal Robots)
- "robotics" first introduced by Isaac Asimov in his science fiction writing
- It is most likely a combination of "rabota" (obligatory work) and "robotnik" (serf).
- The kind of robotics we will talk about will move far beyond such "obligatory work."

Alternative terms

- UAV: Unmanned Aerial Vehicle
- UGV: Unmanned Ground Vehicle
- UUV: Unmanned Undersea (underwater) Vehicle
- AUV: Autonomous Underwater Vehicle

What is a Robot?

- A robot is a system which exists in the *physical* world and *autonomously* *senses* its environment and *acts* in it to achieve some goals.

Other Definitions

- A robot is a re-programmable, multi-functional, manipulator designed to move material, parts, or specialized devices though variable programmed motions for the performance of a task (Robotics Industry Association)

- Robotics is the intelligent connection of perception to action (M. Brady)

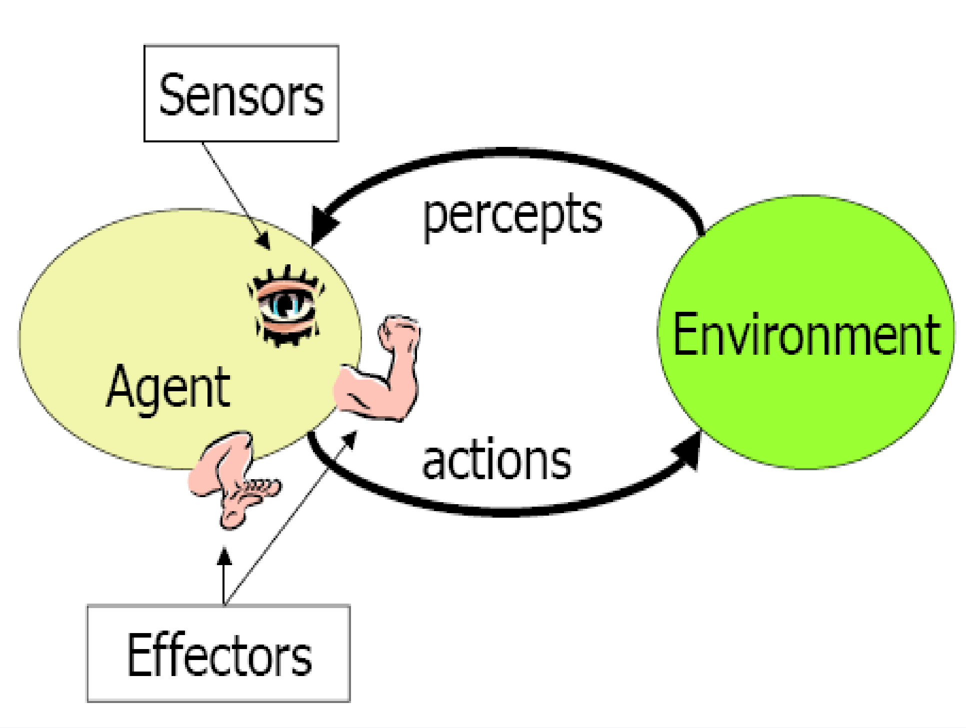
What Makes a Robot?

A robot consists of:

- sensors
- effectors/actuators
- (communication)
- controller

A robot is capable of:

- acting autonomously
- achieving goals



Sensors: what can be sensed?

- Depends on the sensors on the robot
- The robot exists in its *sensor space*: all possible values of sensory readings
- Also called *perceptual space*
- Robot sensors are very different from biological ones
- A roboticist has to try to imagine the world in the robot's sensor space

State: what can be known?

- A sufficient description of the system
- can be:
  - *Observable*: robot always knows its state
  - *Hidden/inaccessible/unobservable*: robot never knows its state
  - *Partially observable*: the robot knows a part of its state
  - *Discrete* (e.g., up, down, blue, red)
  - *Continuous* (e.g., 3.765 mph)

Types of State

- *External state*: state of the world
  - Sensed using the robot's sensors
  - E.g.: night, day, at-home, sleeping, sunny
- *Internal state:* state of the robot
  - Sensed using internal sensors
  - Stored/remembered
  - E.g.: velocity, mood
- The robot's state is a <u>combination</u> of its external and internal state.

State and Intelligence

- *State space*: all possible states the system can be in
- *A challenge*: sensors do not provide state!
- *How intelligent a robot appears is strongly dependent on how much it can sense about its environment and about itself.*

Internal Models

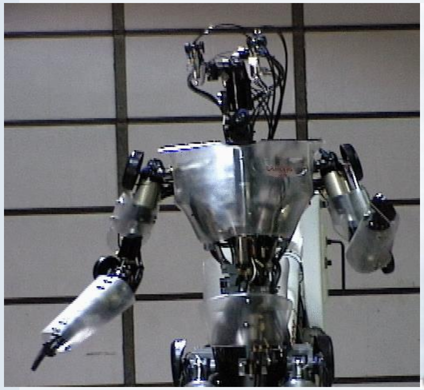
- Internal state can be used to remember information about the world (e.g., remember paths to the goal, remember maps, remember friends v. enemies, etc.)
- This is called a *representation* or an *internal model*.
- *Representations/models have a lot to do with how complex a controller is!*

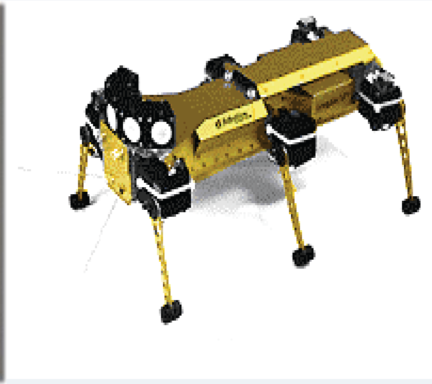
Action/Actuation

- A robot acts through its *actuators* (e.g., motors), which typically drive *effectors* (e.g., wheels)
- Robotic actuators are very different from biological ones, both are used for:
  - *locomotion* (moving around, going places)
  - *manipulation* (handling objects)
- This divides robotics into two areas
  - mobile robotics
  - manipulator robotics

Actuators and DOF

- Mobile robots move around using wheels, tracks, or legs
- Mobile robots typically move in 2D (but note that swimming and flying is 3D)
- Manipulators are various robot arms
- They can move from 1 to many D
- Think of the dimensions as the robot's *degrees of freedom (DOF)*






Action vs. Behavior

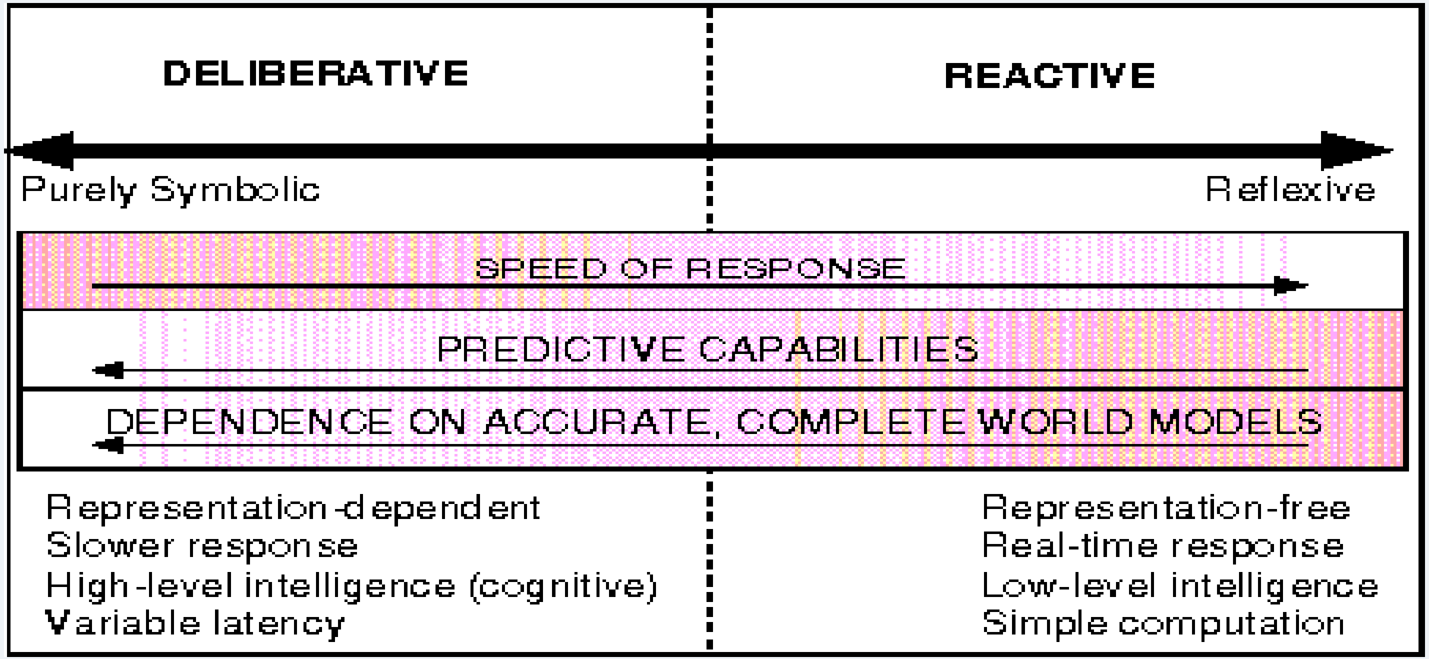
- *Behavior* is what an external observer sees a robot doing.
- Robots are programmed to display desired behavior.
- Behavior is a result of a sequence of robot actions.
- Observing behavior may not tell us much about the internal control of a robot. Control can be a black box.

Autonomy

- *Autonomy is the ability to make one's own decisions and act on them.*
- For robots, autonomy means the ability to sense and act on a given situation appropriately.
- Autonomy can be:
  - *complete (e.g., R2D2)*
  - *partial* (e.g., tele-operated robots)

Control

- *Robot control* refers to the way in which the sensing and action of a robot are coordinated.
- The many different ways in which robots can be controlled all fall along a well-defined *spectrum of control*.



A brief history of robotics

- Feedback control
- Cybernetics
- Artificial Intelligence (AI)
- Early robotics
- Robotics today
  - Why is robotics hard?

Feedback Control

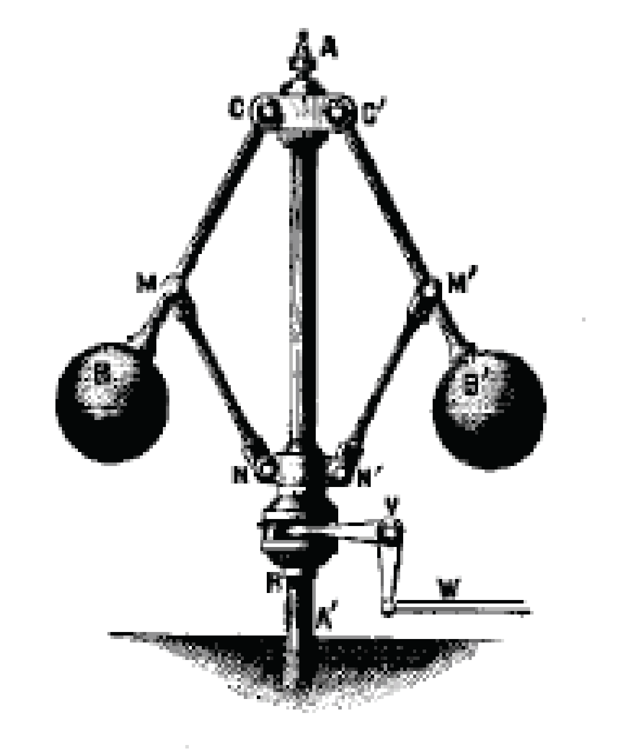
- ***Feedback***: *continuous monitoring of the sensors and reacting to their changes.*
- Feedback control = self-regulation
- Two kinds of feedback:
  - Positive
  - Negative
- The basis of control theory

− and + Feedback

- *Negative feedback*
  - acts to regulate the state/output of the system
  - e.g., if too high, turn down, if too low, turn up
  - thermostats, toilets, bodies, robots...
- *Positive feedback*
  - acts to amplify the state/output of the system
  - e.g., the more there is, the more is added
  - lynch mobs, stock market, ant trails...

Uses of Feedback

- Invention of feedback as the first simple robotics (does it work with our definition)?
- The first example came from ancient Greek water systems (toilets)
- Forgotten and re-invented in the Renaissance for ovens/furnaces
- Really made a splash in Watt's steam engine

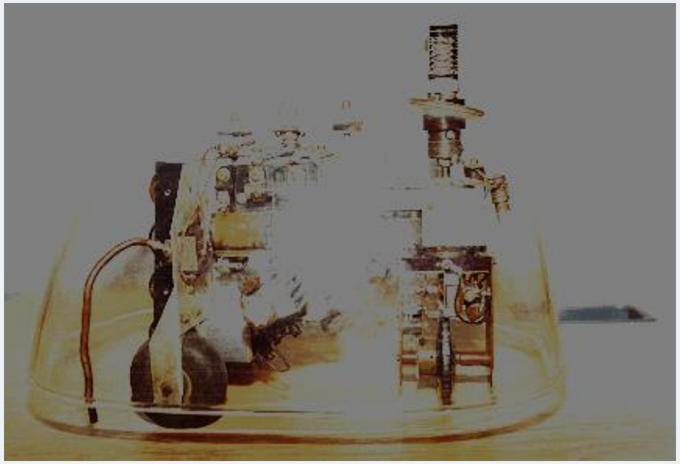


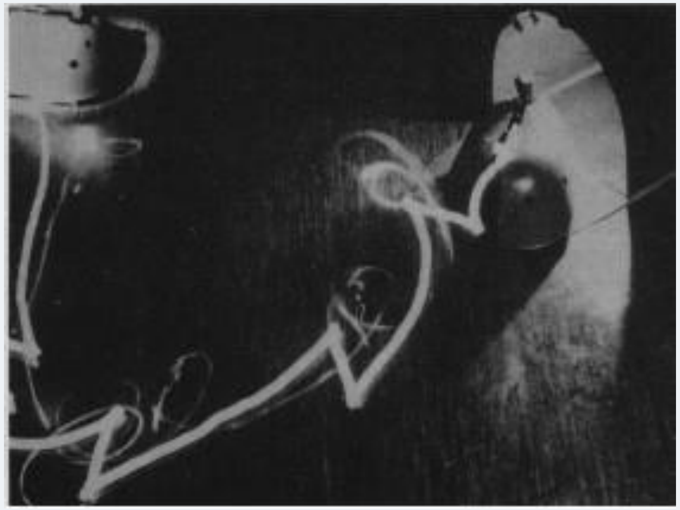
Cybernetics

- Pioneered by Norbert Wiener (1940s)
  - (From Greek "steersman / governor" of steam engine)
- Marriage of control theory (feedback control), information science and biology
- Seeks principles common to animals and machines, especially for control and communication
- Coupling an organism and its environment (*situatedness*)

W. Grey Walter's Tortoise (1950's)

- *Machina Speculatrix*
- 1 photocell & 1 bump sensor, 1 motor
- Behaviors:
  - seek light
  - head to weak light
  - back from bright light
  - turn and push
  - recharge battery
- Reactive control





The Walter Turtle in Action

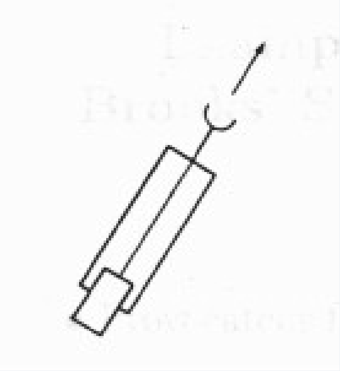
Braitenberg’s Vehicles

- Valentino Braitenberg (early 1980s)
- Extended Walter’s model in a series of thought experiments
- Also based on analog circuits
- Direct connections (excitatory or inhibitory) between light sensors and motors
- Complex behaviors from very simple mechanisms

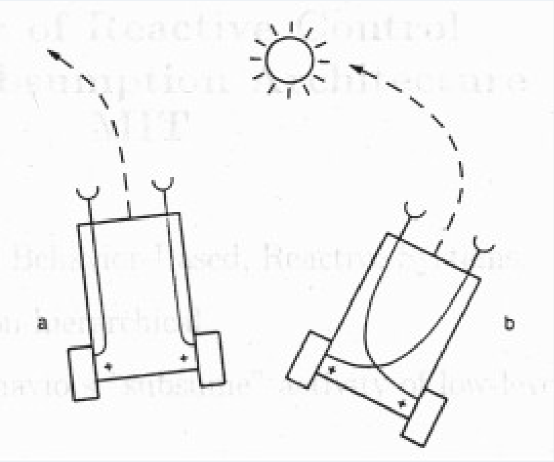
Braitenberg’s Vehicles

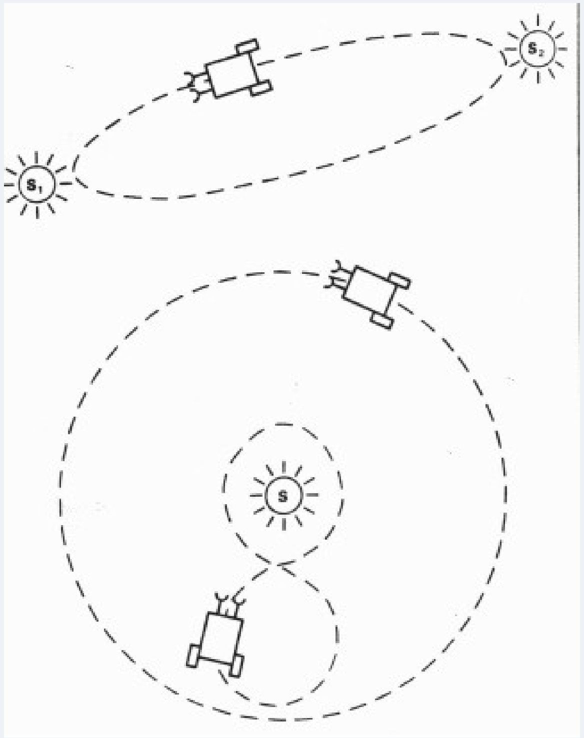
- Examples of Vehicles:

V1:



V2:





Braitenberg's Vehicles

- By varying the connections and their strengths, numerous behaviors result, e.g.:
  - "fear/cowardice" - flees light
  - "aggression" - charges into light
  - "love" - following/hugging
  - many others, up to memory and learning!

- Reactive control
- Later implemented on real robots

Early Artificial Intelligence

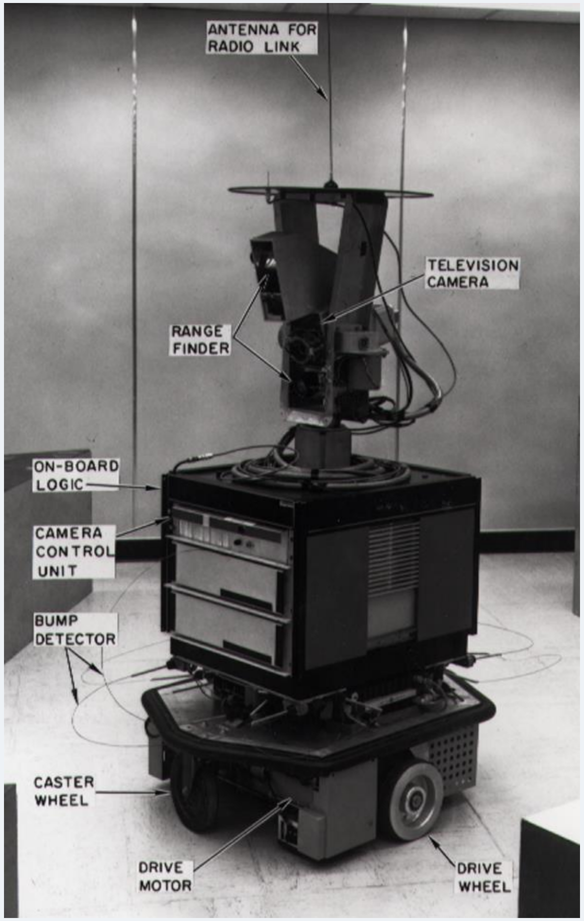
- "Born" in 1955 at Dartmouth
- "Intelligent machine" would use internal models to search for solutions and then try them out (M. Minsky) => deliberative model!
- *Planning* became the tradition
- Explicit symbolic representations
- Hierarchical system organization
- Sequential execution

Artificial Intelligence (AI)

- Early AI had a strong impact on early robotics
- Focused on knowledge, internal models, and reasoning/planning
- Basis of deliberative control in early robots

Early Robots: SHAKEY

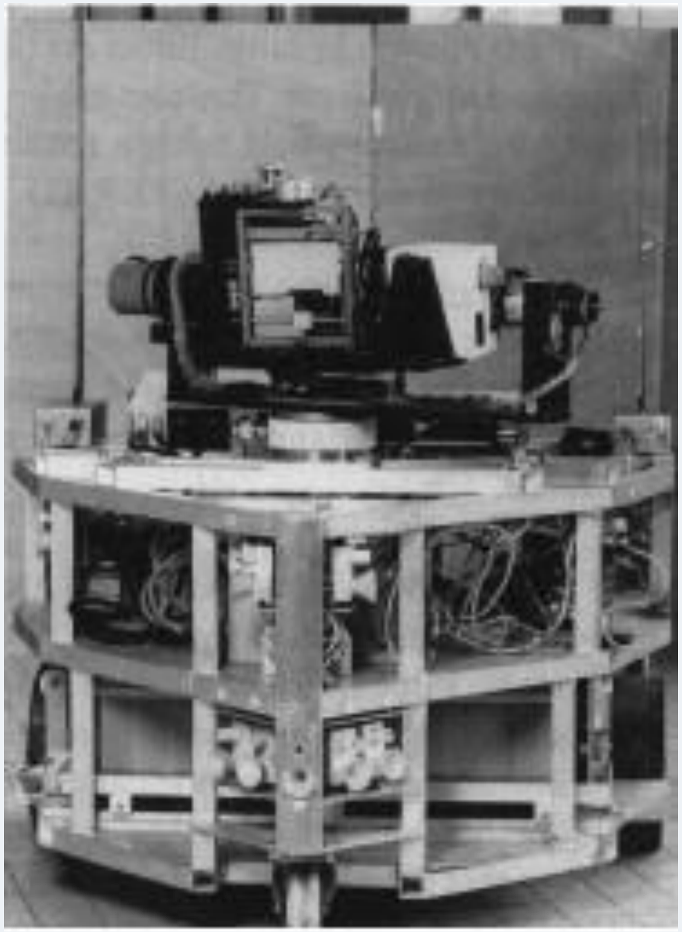
- At Stanford Research Institute (late 1960s)
- Vision and contact sensors
- STRIPS planner
- Visual navigation in a special world
- Deliberative



1972 model

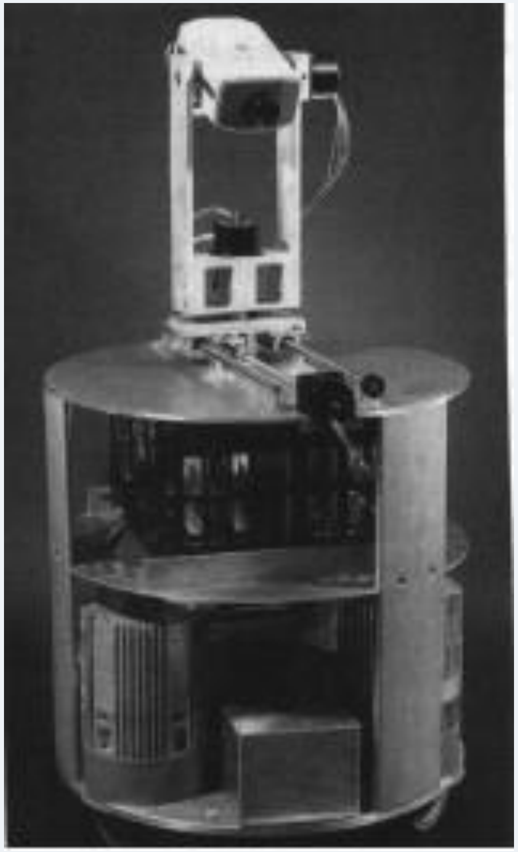
Early Robots: HILARE

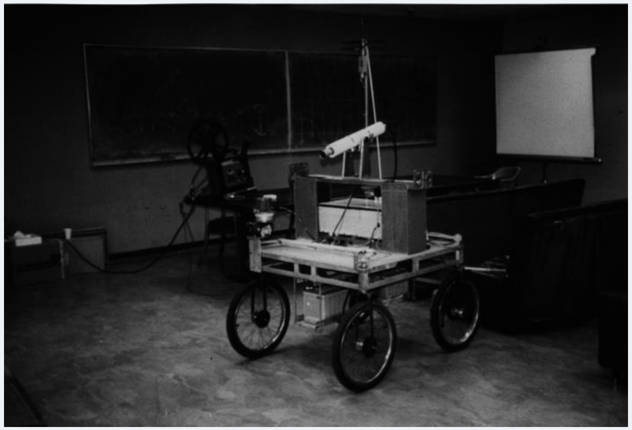
- LAAS in Toulouse, France (late 1970s)
- Video, ultrasound, laser range-finder
- Still in use!
- Multi-level spatial representations
- Deliberative -> Hybrid Control



Early Robots: CART/Rover

- Hans Moravec
- Stanford Cart (1977) followed by CMU rover (1983)
- Sonar and vision
- Deliberative control





What’s the problem?

- Robot is slow in deliberation
  - Based on the *sense->plan->act* (SPA) model
  - Inherently sequential
  - Planning requires search, which is slow
  - Search requires a world model
  - World models become outdated
  - Search and planning takes too long

Reactive Systems

- Collections of *sense-act (stimulus-response) rules*
  - Inherently *concurrent (parallel)*
  - No/minimal state
  - No memory
  - Very fast and reactive
  - Unable to plan ahead
  - Unable to learn
- Sentinel papers:
  - Brooks, R. A., Intelligence Without Reason
  - Brooks, R.A., A robust layered control system for a mobile robot.

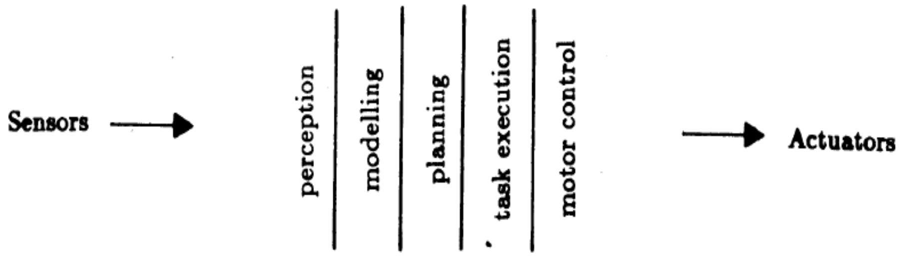


Figure 1. A traditional decomposition of a mobile robot control system into functional modules.

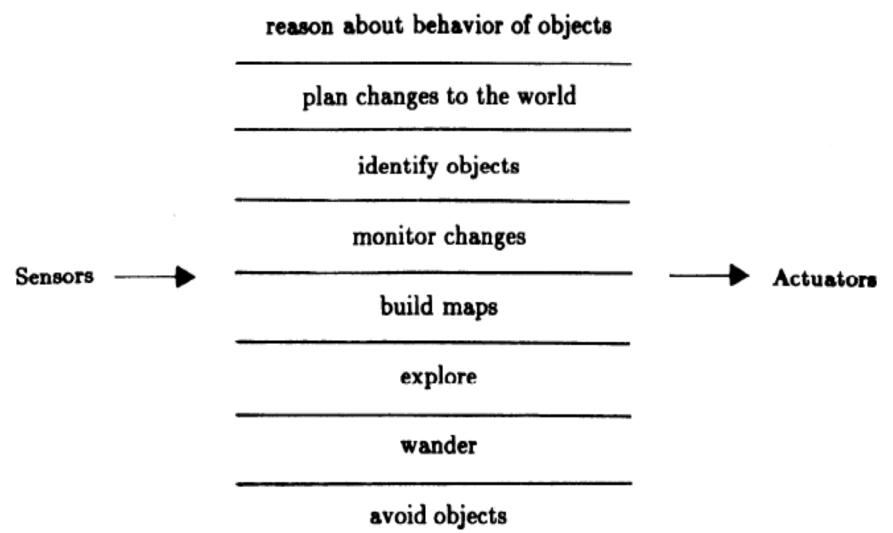
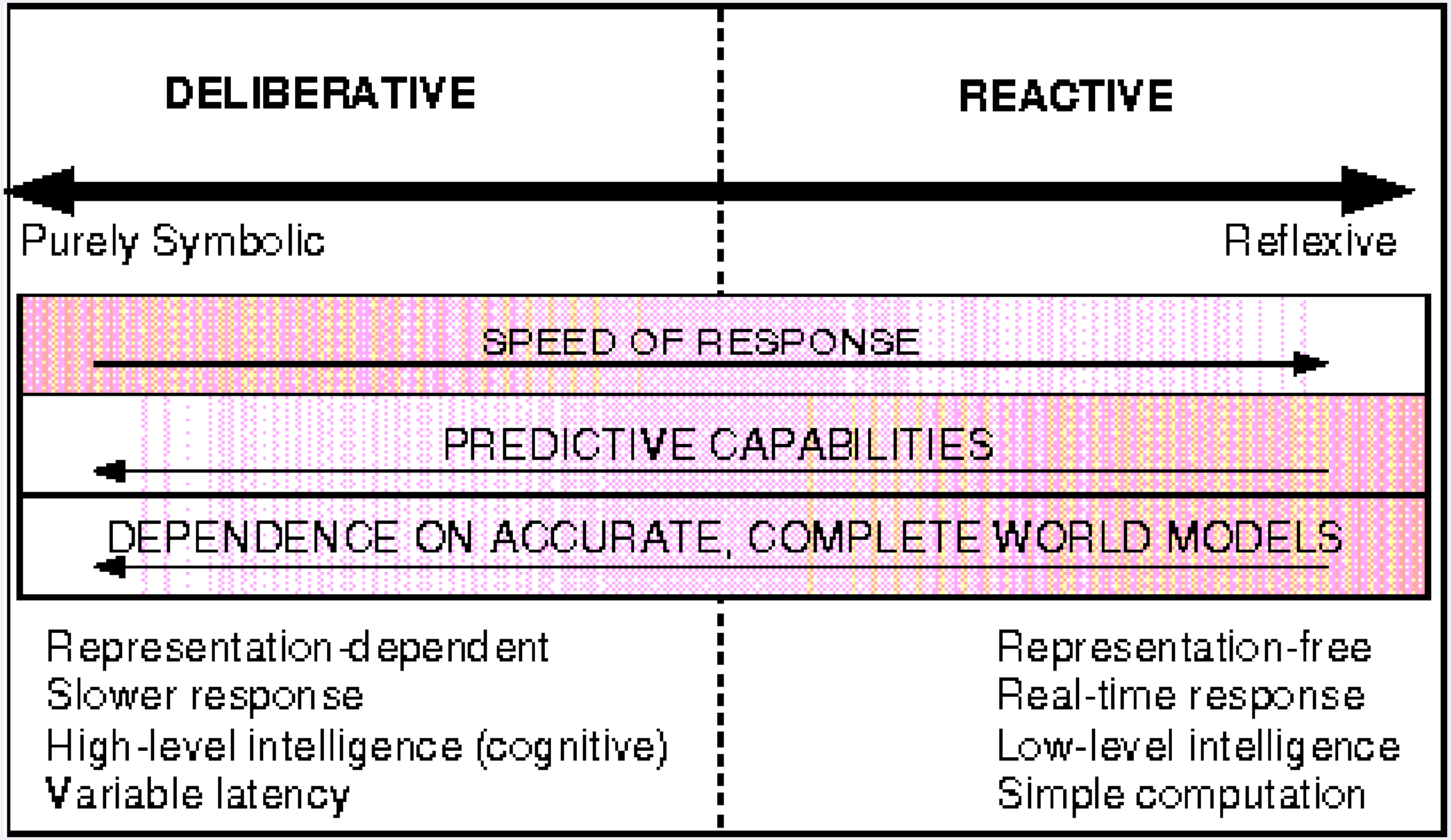


Figure 2. A decomposition of a mobile robot control system based on task achieving behaviors.

Spectrum of Control



Hybrid Systems

- Combine the two extremes
  - reactive system on the bottom
  - deliberative system on the top
  - connected by some intermediate layer
- Often called 3-layer systems
- Layers must operate *concurrently*
- Different *representations and time-scales* between the layers
- The best or worst of both worlds?

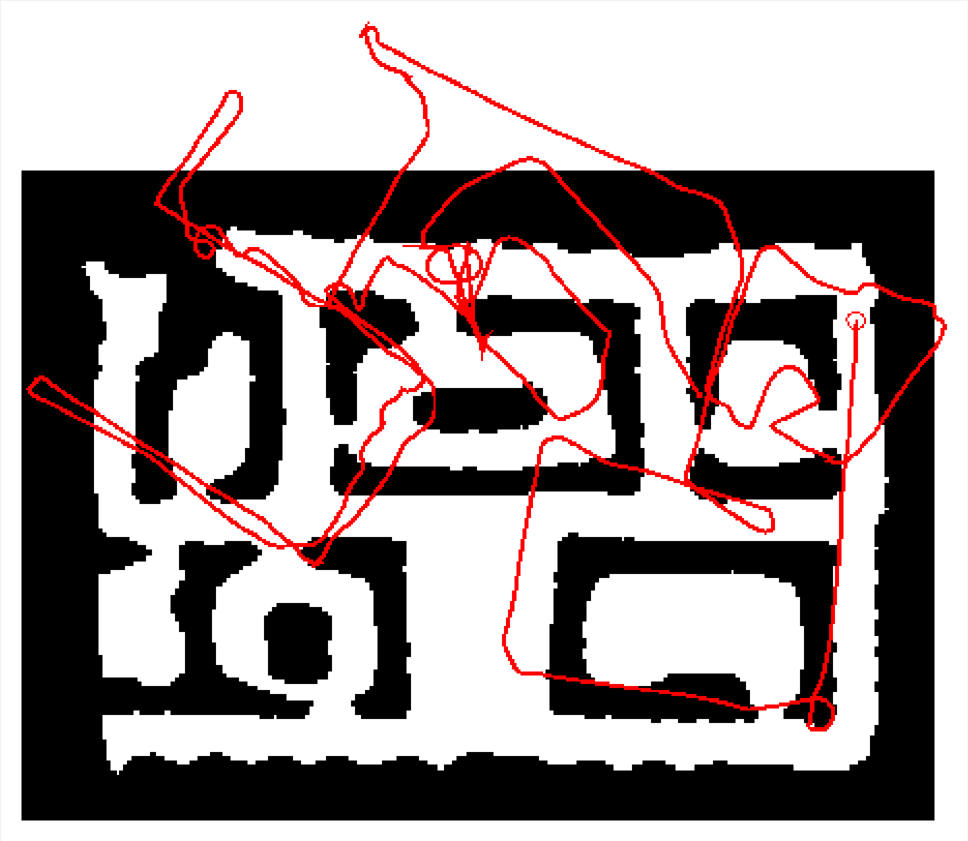
Behavior-Based Systems

- An alternative to hybrid systems
- Have the same capabilities
  - the ability to act reactively
  - the ability to act deliberatively
- There is no intermediate layer
- A unified, consistent representation is used in the whole system=> *concurrent behaviors*
- That resolves issues of time-scale

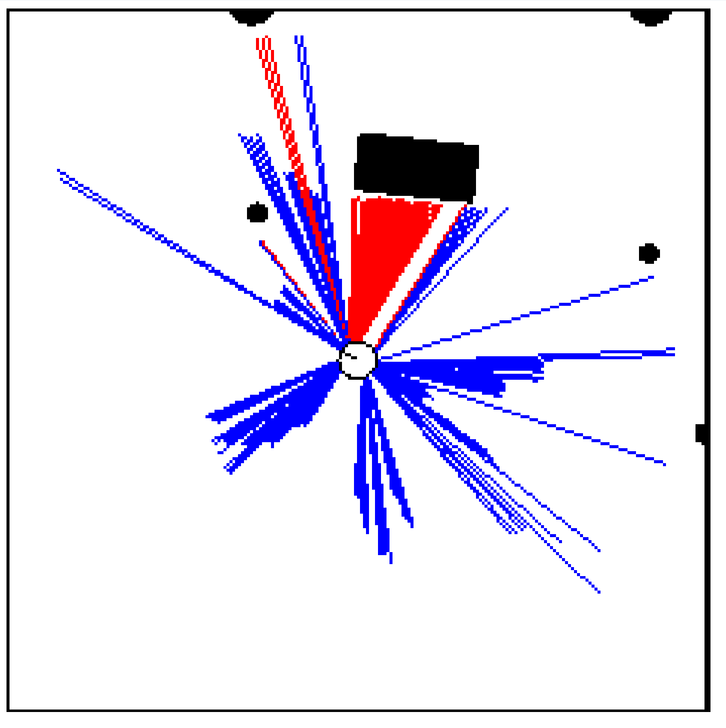
So, are we done?

- Sensors are limited and crude
- Effectors are limited and crude
- State (internal and external, but mostly external) is partially-observable
- Environment is dynamic (changing over time)
- Environment is full of potentially-useful (and useless) information

Nature of Sensor Data



Odometry Data



Range Data

Probabilistic Robotics

- Address the fundamental problem of robotics i.e. *how to combat uncertainty* using the tools of probability theory
- The need to model errors from sensors, actuators, and dynamic environment.

$$P(x, y) = P(x \mid y) P(y) = P(y \mid x) P(x)$$

$$\Rightarrow$$

$$P(x \mid y) = \frac{P(y \mid x)\ P(x)}{P(y)} = \frac{\text{likelihood} \cdot \text{prior}}{\text{evidence}}$$

Recursive Bayesian Updating

state observations

$$P(x \mid z_1, \dots, z_n) = \frac{P(z_n \mid x, z_1, \dots, z_{n-1}) \, P(x \mid z_1, \dots, z_{n-1})}{P(z_n \mid z_1, \dots, z_{n-1})}$$

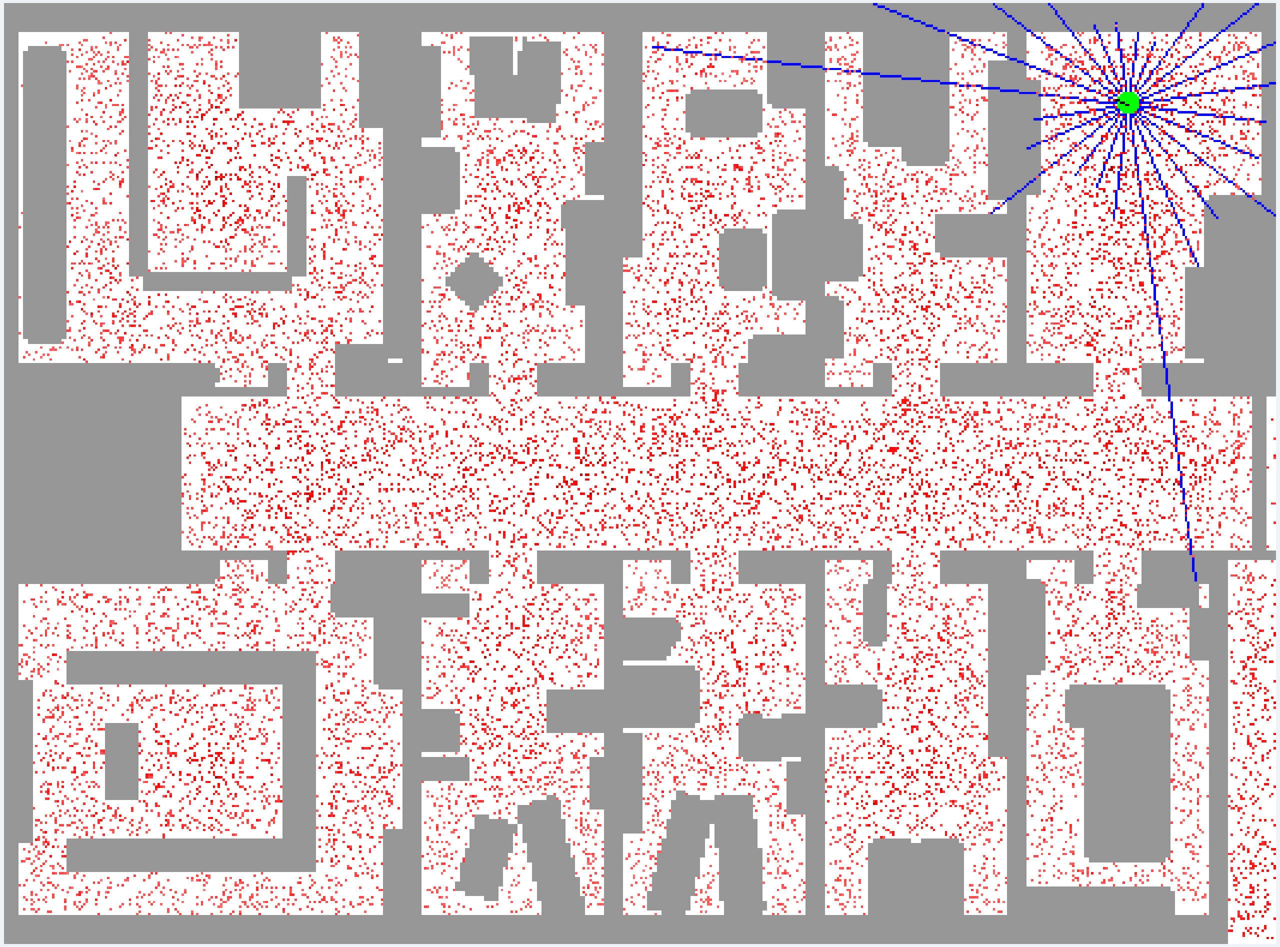
Markov assumption: z_n is independent of $z_1, \dots, z_{n-1}$ if we know x.

$$P(x \mid z_1, \dots, z_n) = \frac{P(z_n \mid x) \, P(x \mid z_1, \dots, z_{n-1})}{P(z_n \mid z_1, \dots, z_{n-1})}$$

$$= \eta \, P(z_n \mid x) \, P(x \mid z_1, \dots, z_{n-1})$$

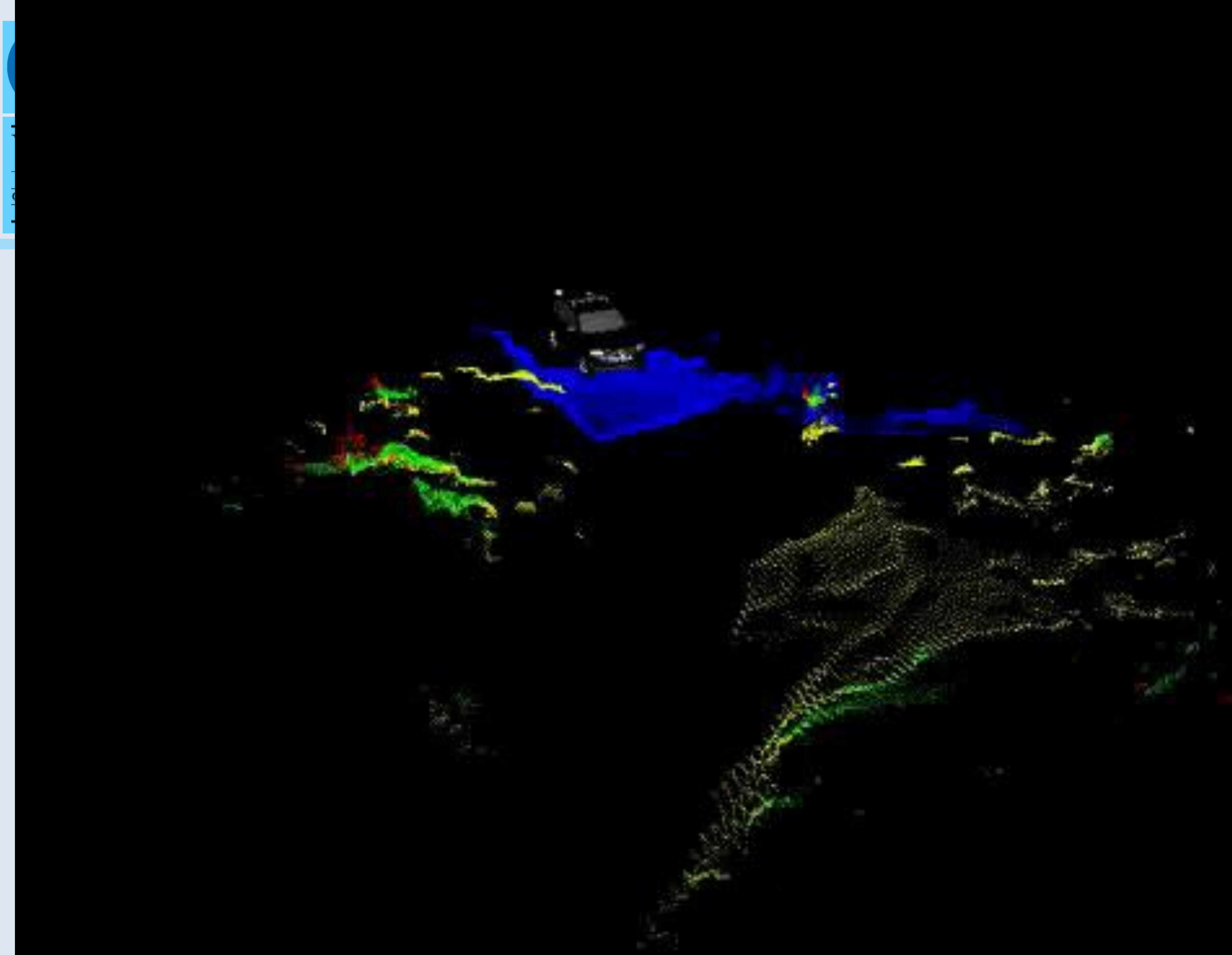
$$= \eta_{1 \dots n} \prod_{i=1 \dots n} P(z_i \mid x) \, P(x)$$

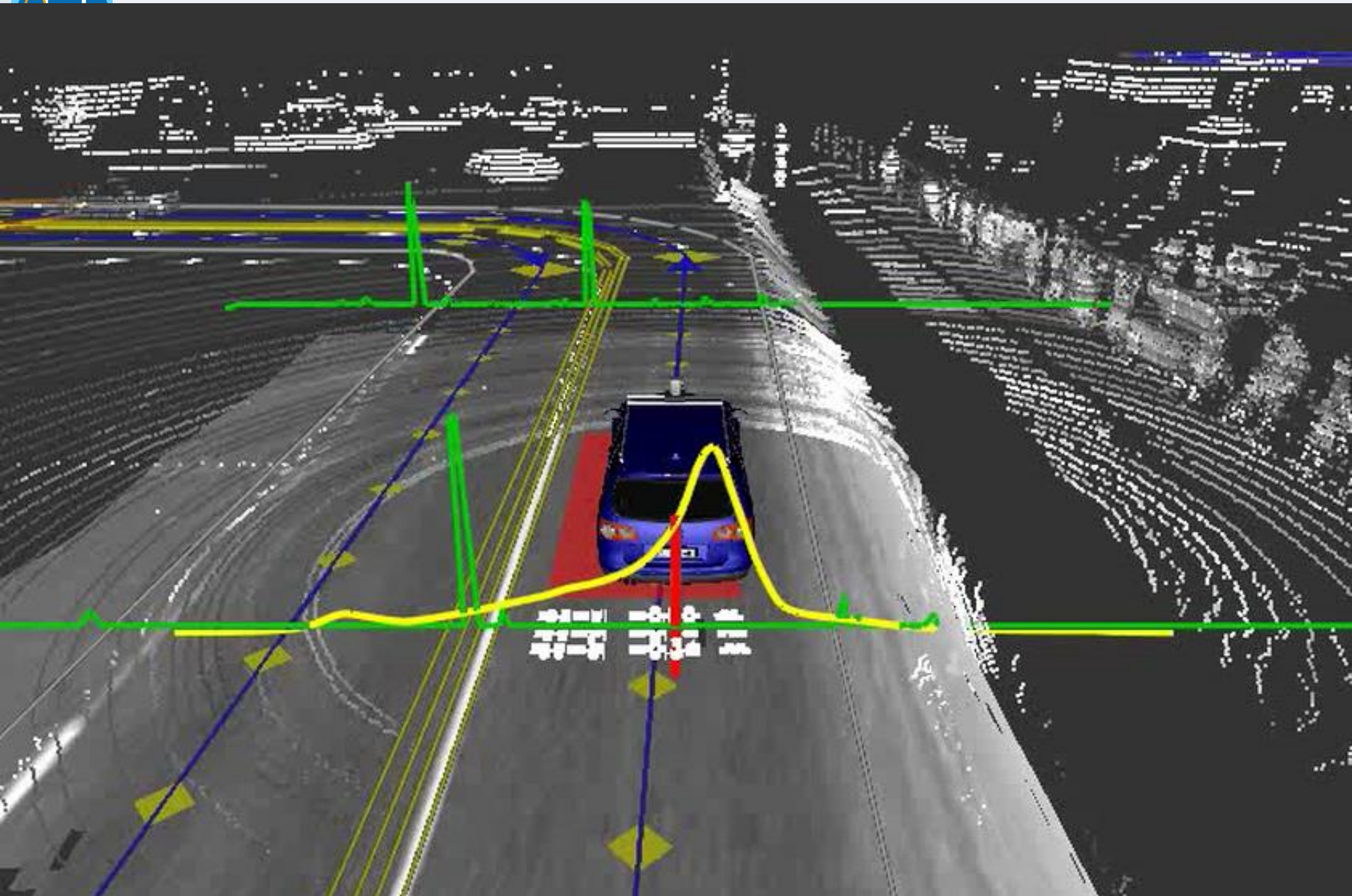
Localization



Navigation Challenges

- Moving from place to place
- Why is navigation hard?
  - Limitations and errors in sensing
  - Uncertainty in localization (where am I?)
  - Uncertainty in map or no map
  - Uncertainty in actuation





Navigation Involves

- Localization
- Path planning
- Search / coverage
- Mapping
- Simultaneous Localization and Mapping (SLAM)

Localization

- Have a map of the world, need to figure out where you are on the map.

- Can use:
  - Global knowledge - GPS
  - Dead-reckoning - odometry
  - Landmark detection
- Problems:
  - Estimation process is indirect
  - Measurements are noisy
  - Measurements are not always available

Landmark Detection

- Compare view of world as perceived by sensors to stored world model - try to find a match

- Examples:
  - Laser scans - scan matching
  - Vision - visual landmarks

- Problems:
  - Output from sensors needs to match the format of the world model representation. (eg difficult to use vision to match to a sonar-built map)
  - Data association - may parts of the environment look the same
  - Environment changes - world model becomes outdated (e.g., change in lighting -> shadows change -> vision problems)

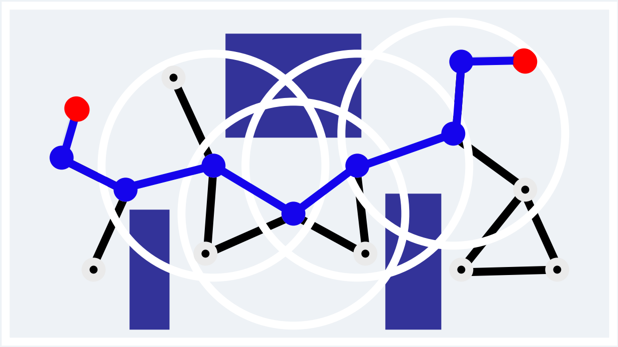
Path Planning

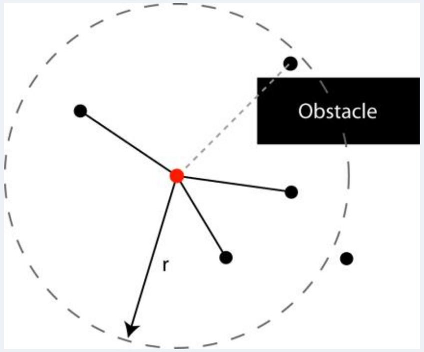
- Finding a route from start to goal location
- Need a map / world model
- Need localization
- World is often represented as a graph (topological map)
- Use graph search techniques to find path (e.g., A*)

- Problems:
  - Searching is slow
  - Dynamic environment -> world model outdated -> need to detect changes and re-plan new route.

Planning Example - PRM

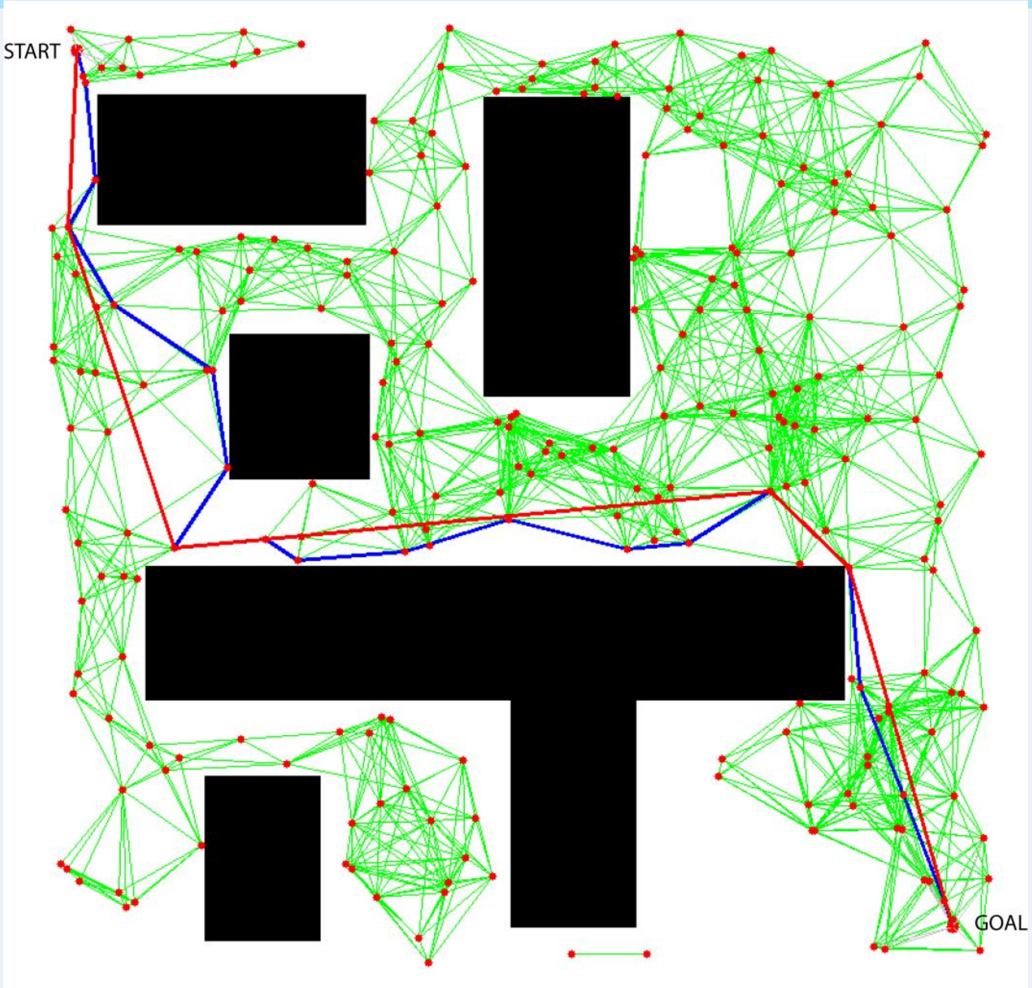
- Probabilistic Roadmaps
  - Map Building Phase
    - Randomly add nodes to C_{free}
    - Attempt to connect to other nodes (local planner)
  - Query Phase
    - Connect start and goal to map
    - Use A* to find path from start to goal





Local Planner

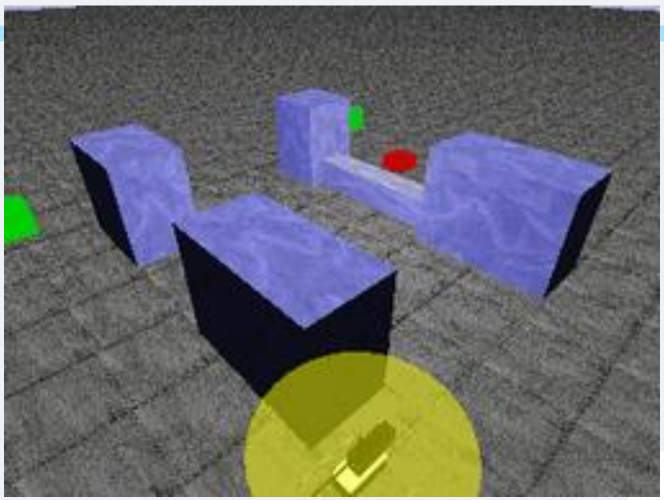
PRM Result



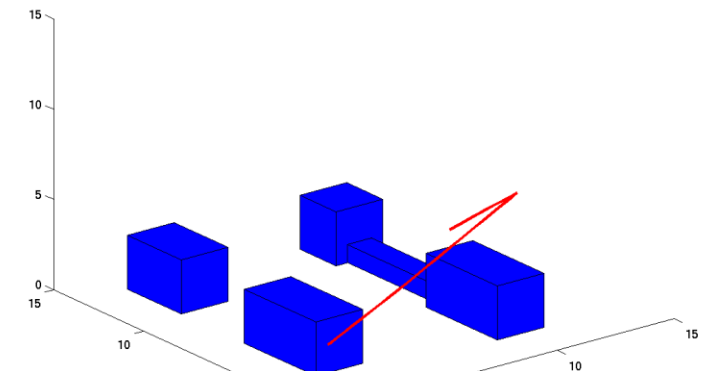
Original path

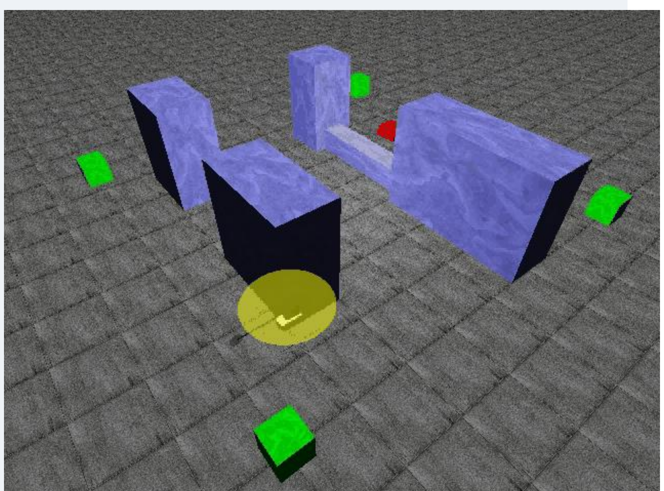
After path smoothing

3D PRM results

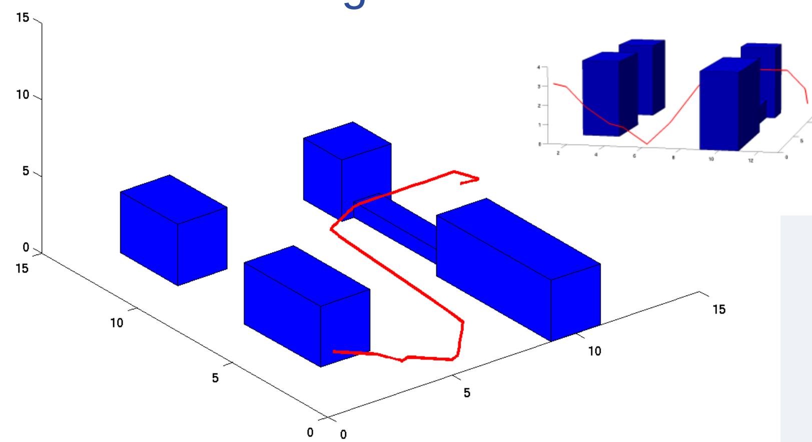


No Height Constraint





4m Height Constraint



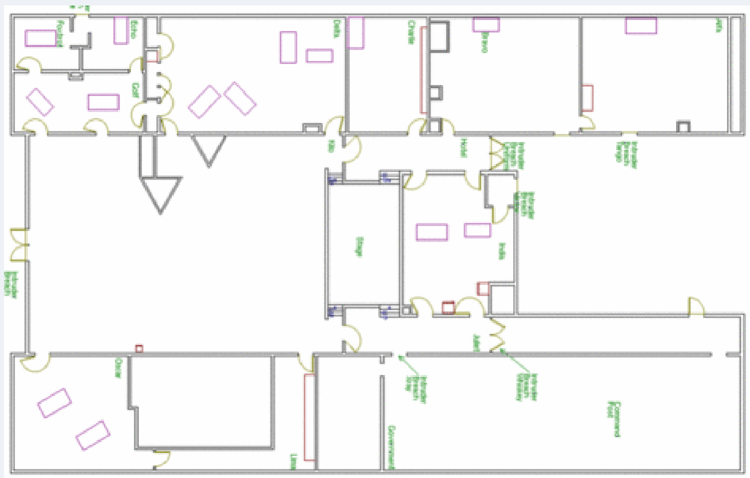
SLAM

- SLAM: simultaneous localization and mapping
- To start - no map and don't know where you are
- "Chicken and egg" problem: Need map to localize, but can't build a map if you aren't localized
- Solution: Run mapping and localization in parallel - as map accuracy improves, localization improves, which improves the map, and so on

Coverage and Exploration

- Try to explore an unknown area
- Try to find something in an area
- With map - can plan a path that covers the area
- Without map - try to move in a systematic manner
  - Follow boundaries
  - Spiral outward
  - Random motion
  - E.g. - Roomba

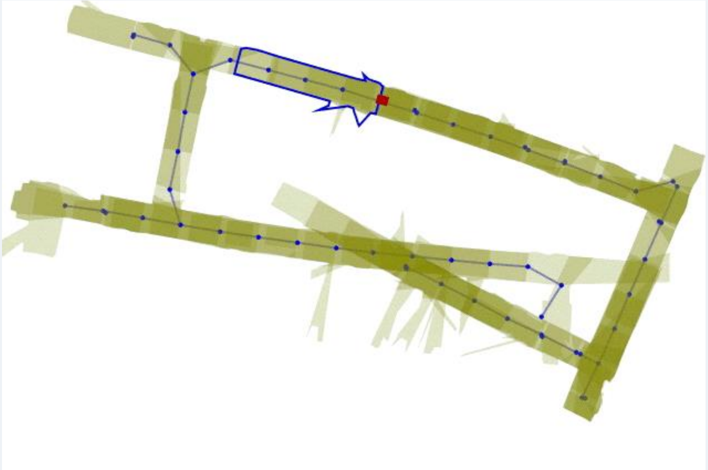
Example Exploration Results



Common Navigation Challenges

- Kidnapped Robot
  - Robot is localized, but is then moved (without being told)
  - Now it thinks it is still somewhere else - needs to re-localize

- Closing the loop
  - When building a map, robot returns to the same place via another route - needs to realize this is the same place, and not a new area.



Monte Carlo Localization

- the probability density function is represented by samples
- randomly drawn from it
- it is also able to represent multi-modal distributions, and thus localize the robot *globally*
- considerably reduces the amount of memory required and can integrate measurements at a higher rate
- state is not discretized and the method is more accurate than the grid-based methods
- easy to implement

"Probabilistic Robotics"

- Sebastian Thrun

- Bayes' rule

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

- Definition of *marginal* probability

$$p(A) = \sum_{\text{all } B} p(A \wedge B)$$

$$p(A) = \sum_{\text{all } B} p(A \mid B) \cdot p(B)$$

- Definition of *conditional* probability iLab

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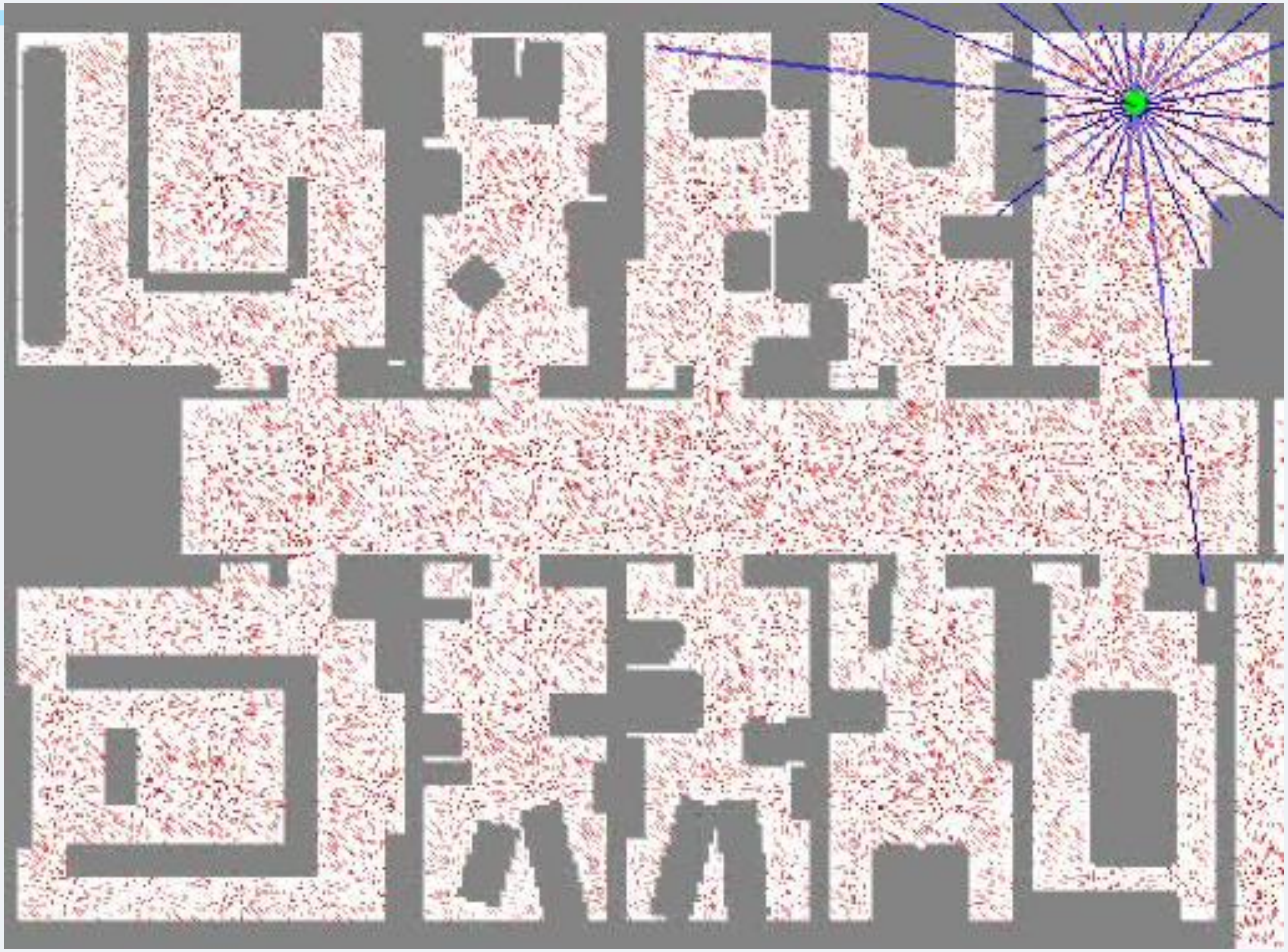
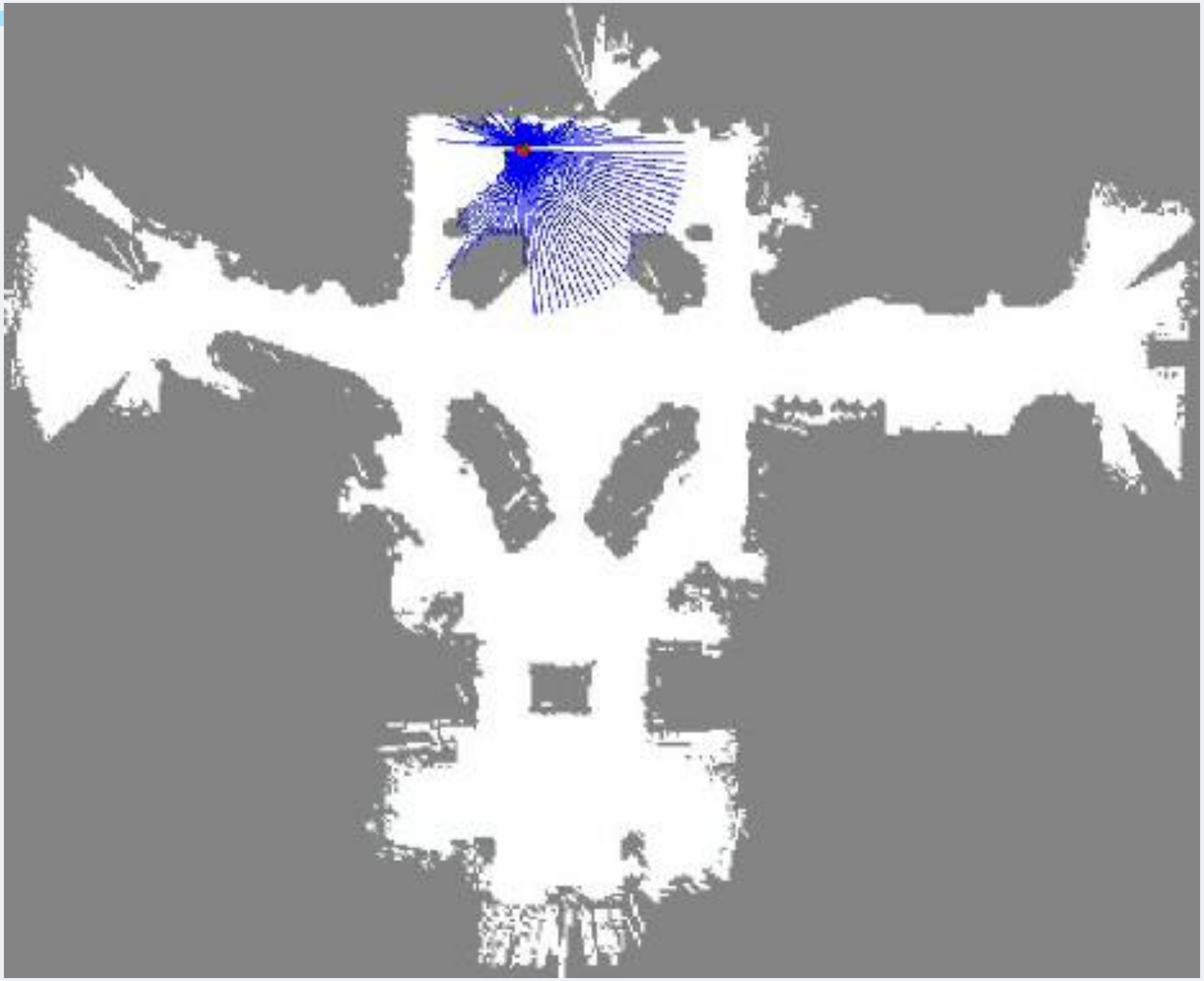
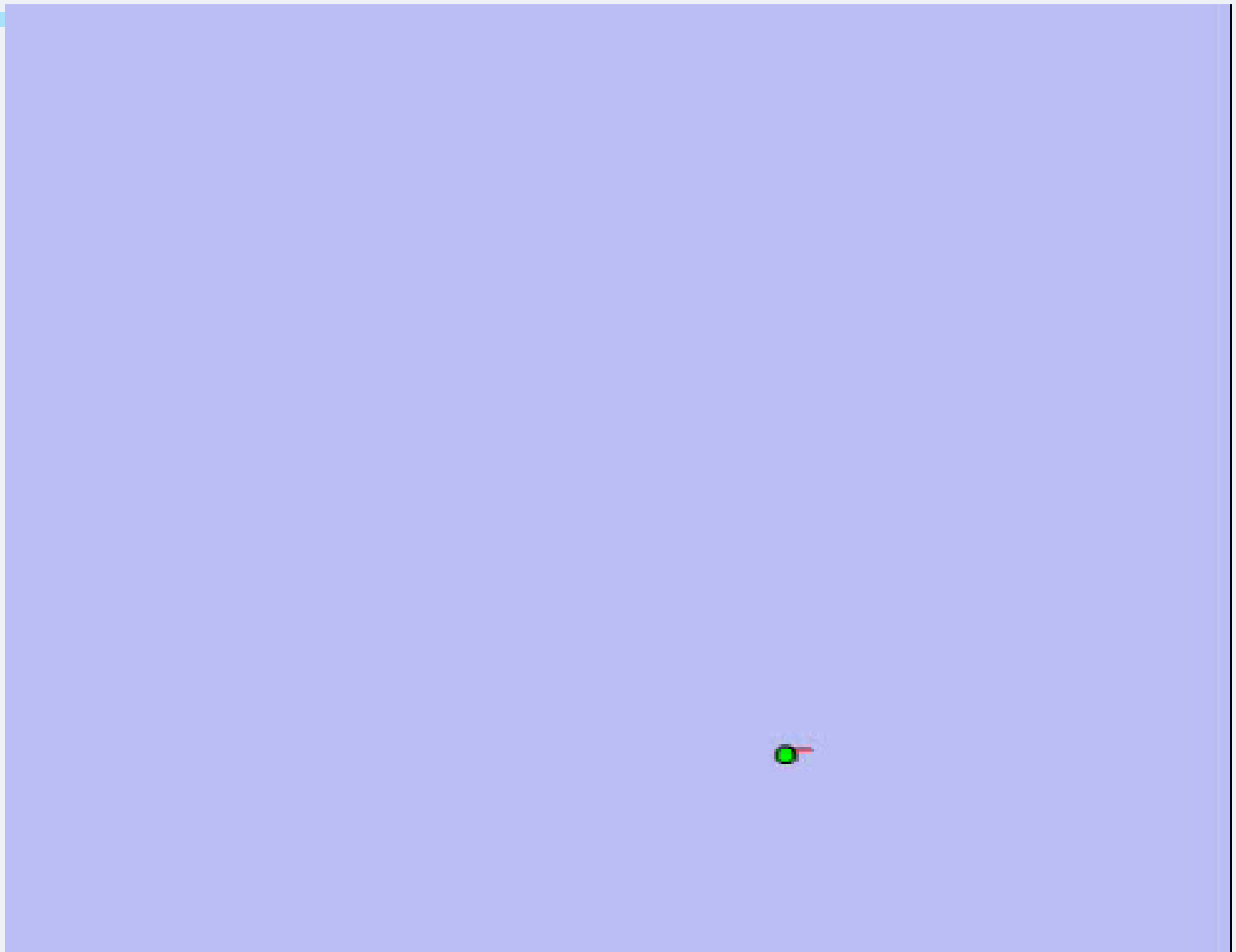
Monte-Carlo localization (Thrun)



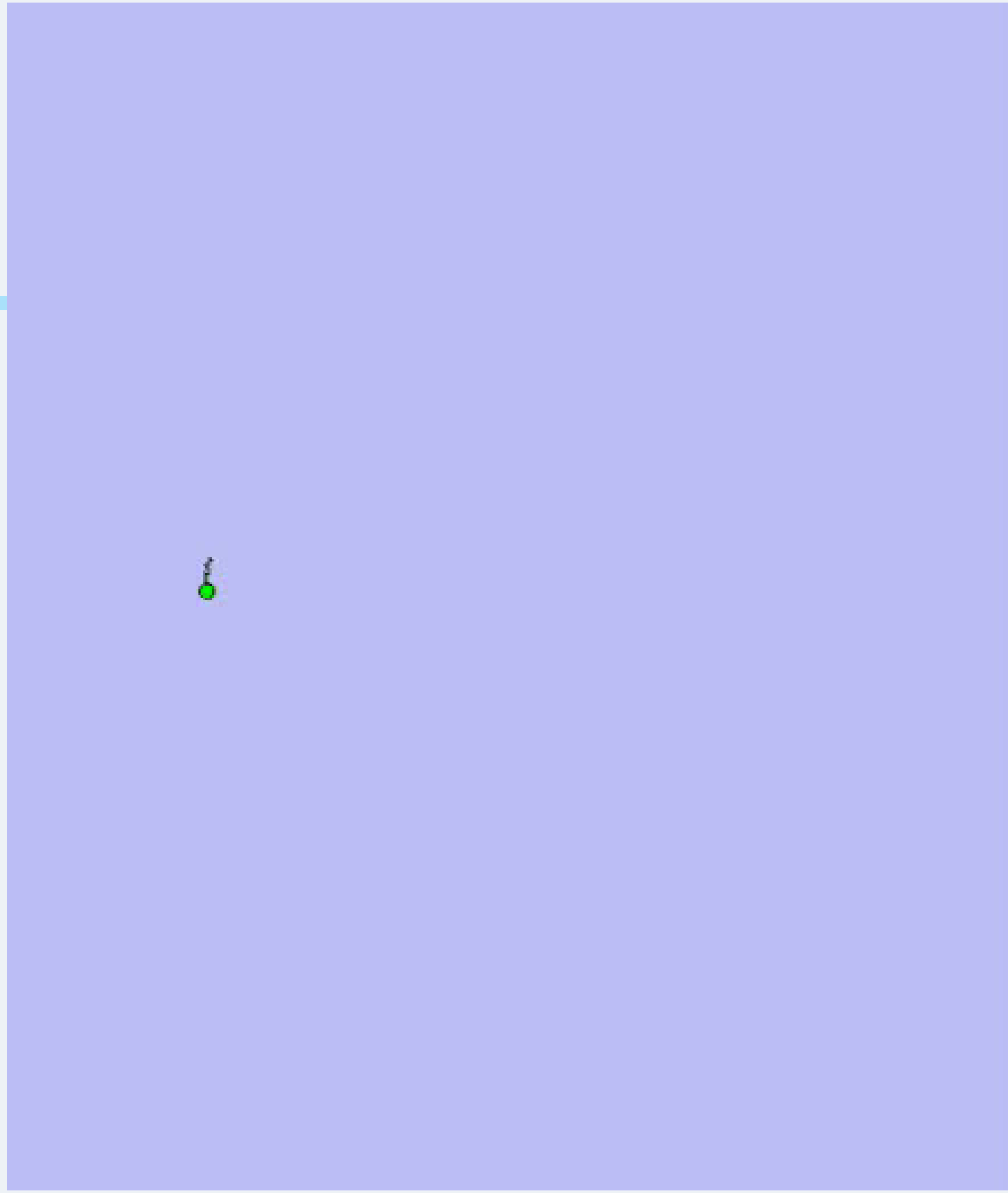
Monte-Carlo Localization



FASTslam (Thrun)



FASTslam

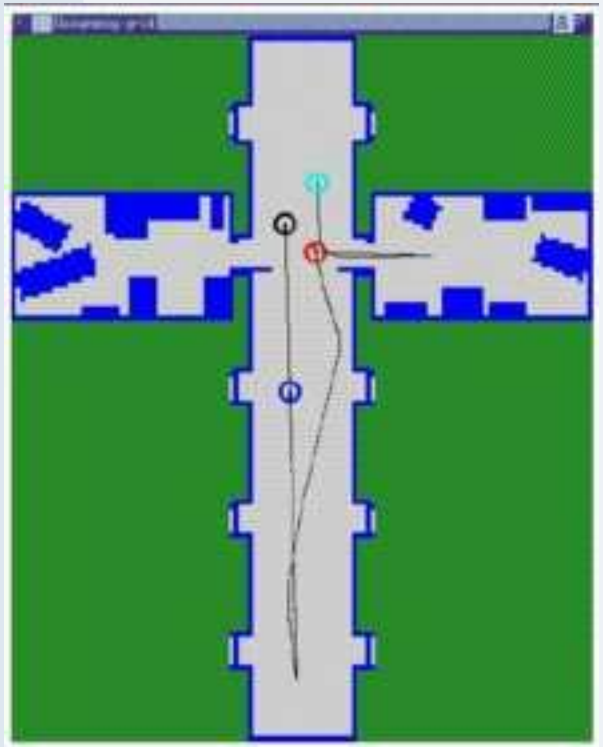


Setting up the problem

(following slides from Jizhong Xiao, CUNY)

The robot does (or can be modeled to) alternate between

- sensing -- getting range observations $o_1, o_2, o_3, \ldots, o_{t-1}, o_t$
- acting -- driving around (or ferrying?) $a_1, a_2, a_3, \ldots, a_{t-1}$



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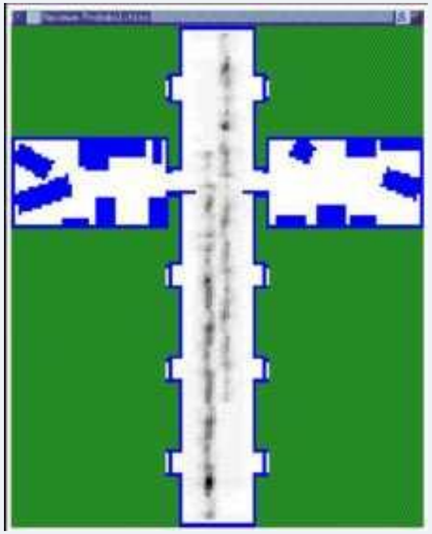
We want to know r_t -- the position of the robot at time t

- but we'll settle for $p(r_t)$ -- the probability distribution for r_t

What *kind* of thing is $p(r_t)$?



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We do know m -- the map of the environment

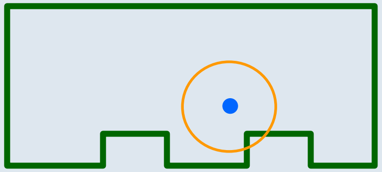
$p(o \mid r, m)$ -- the sensor model

$p(r_{new} \mid r_{old}, a, m)$ -- the accuracy of desired action a

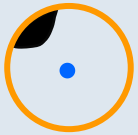
Robot modeling

p(o | r, m) sensor model

map m and location r



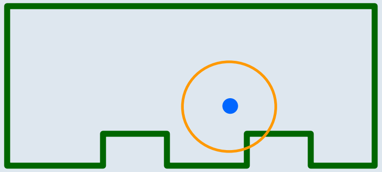
p( | r, m) = .75

p( | r, m) = .05

potential observations o

Robot modeling

$p(\, o \mid r, m\,)$ sensor model



$p(\, r_{new} \mid r_{old}, a, m\,)$ action model

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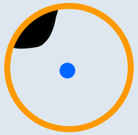
$p($  $\mid r, m\,) = .05$

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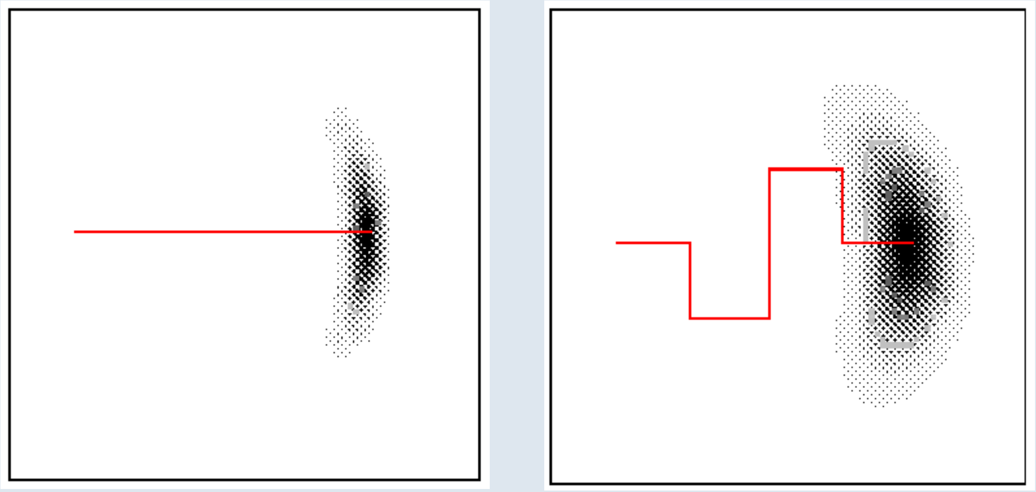

"probabilistic kinematics" -- encoder uncertainty

- red lines indicate commanded action
- the cloud indicates the likelihood of various final states

Robot modeling: how-to

p(o | r, m) sensor model

p(r_{new} | r_{old}, a, m) action model

(0) Model the physics of the sensor/actuators (with error estimates)

theoretical modeling

(1) Measure lots of sensing/action results and create a model from them

empirical modeling

- take N measurements, find mean (m) and st. dev. (σ) and then use a Gaussian model
- or, some other easily-manipulated model...

$$f(x) = \frac{e^{-(x-\mu)^2/(2\sigma^2)}}{\sigma\sqrt{2\pi}}$$

$$p(x) = \begin{cases} 0 & \text{if } |x-m| > \sigma \\ 1 & \text{otherwise} \end{cases}$$

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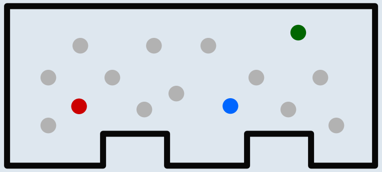
(2) Make something up...

Monte Carlo Localization

Start by assuming $p(r_0)$ is the uniform distribution.



take K samples of r_0 and weight each with an *importance factor* of $1/K$

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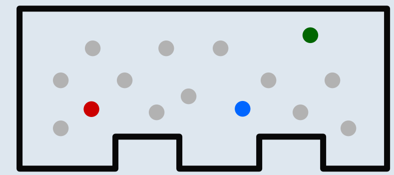

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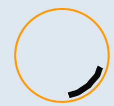
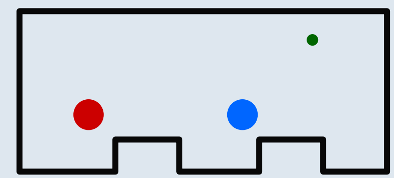
Get the current sensor observation, o_1



For each sample point r_0 multiply the importance factor by $p(o_1 \mid r_0, m)$



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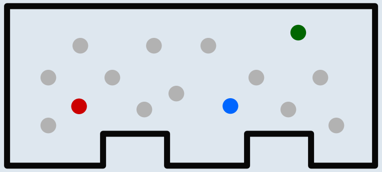

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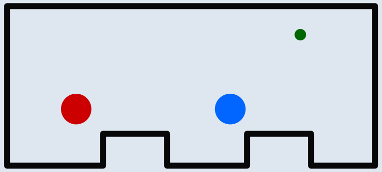
Normalize (make sure the importance factors add to 1)



You now have an approximation of $p(r_1 \mid o_1, \ldots, m)$

and the distribution is no longer uniform

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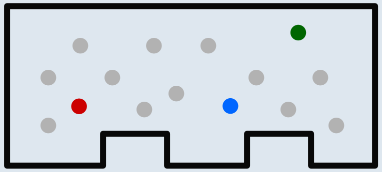

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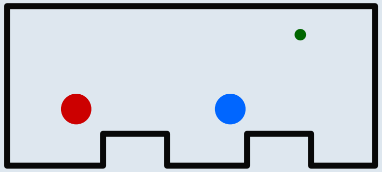

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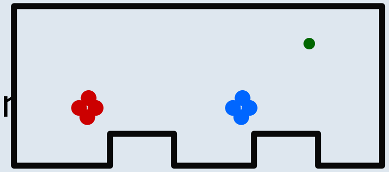
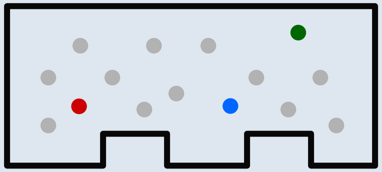
Create r_1 samples by dividing up large clumps



each point spawns new ones in proportion to its importance factor

Monte Carlo Localization



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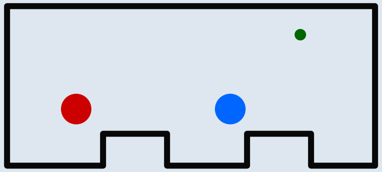

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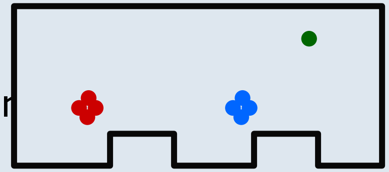

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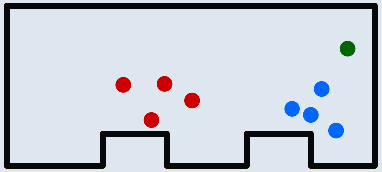
The robot moves, a_1

For each sample r_1, move it according to the model $p(r_2 \mid a_1, r_1, m)$



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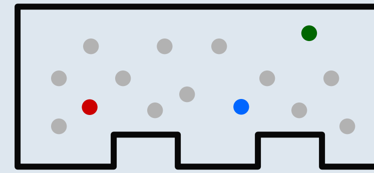

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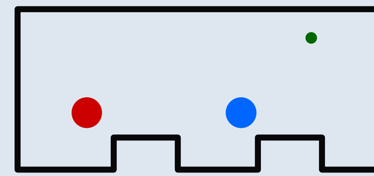

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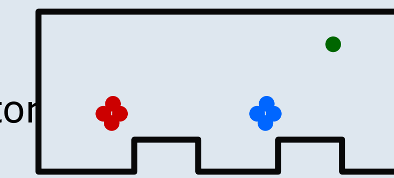

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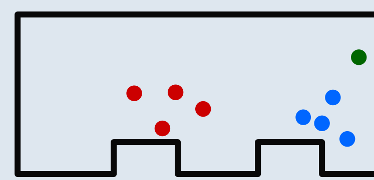
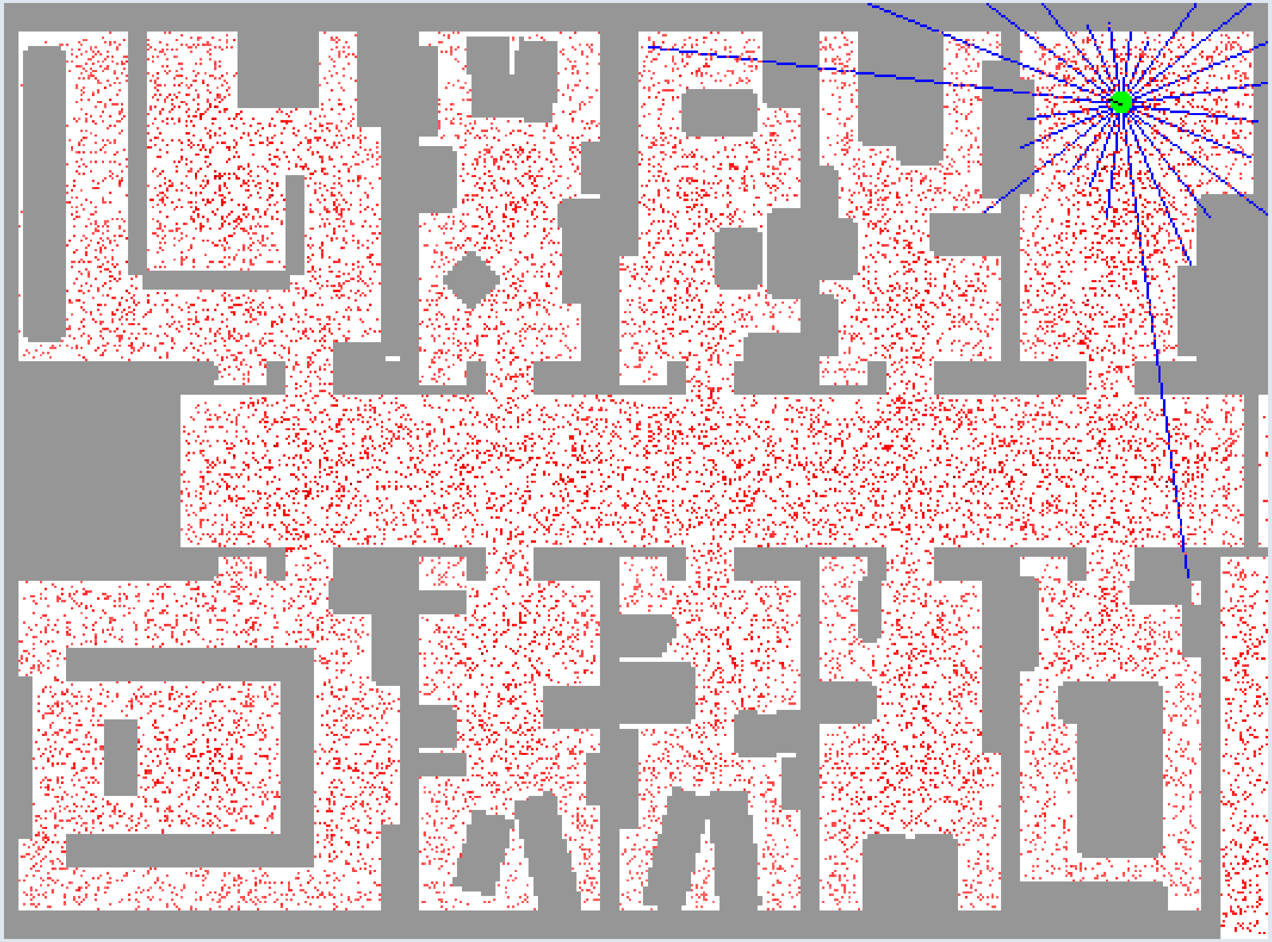


MCL in action

"Monte Carlo" Localization -- refers to the resampling of the distribution each time a new observation is integrated



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