CS 188: Artificial Intelligence
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Advanced Applications:
Robotics

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Announcements

- Practice Final Out (optional)
  - Similar extra credit system as practice midterm
- Contest (optional):
  - Tomorrow night 11pm deadline for final submission
- Project 5 Classification is out: due next week Friday

So Far Mostly Foundational Methods

Advanced Applications

Robotic Control Tasks

- Perception / Tracking
  - Where exactly am I?
  - What’s around me?
- Low-Level Control
  - How to move the robot and/or objects from position A to position B
- High-Level Control
  - What are my goals?
  - What are the optimal high-level actions?

Robot folds towels

[pile of 5 video]

[Maitin-Shapiro, Cusumano-Towner, Lai & Abbeel, 2010]
Low-Level Planning

- Low-level: move from configuration A to configuration B

A Simple Robot Arm

- Configuration Space
  - What are the natural coordinates for specifying the robot’s configuration?
  - These are the configuration space coordinates
  - Can’t necessarily control all degrees of freedom directly

- Work Space
  - What are the natural coordinates for specifying the effector tip’s position?
  - These are the work space coordinates

Coordinate Systems

- Workspace:
  - The world’s (x, y) system
  - Obstacles specified here

- Configuration space
  - The robot’s state
  - Planning happens here
  - Obstacles can be projected to here

Obstacles in C-Space

- What / where are the obstacles?
- Remaining space is free space

Two-link manipulator

- \( x = d_1 \cos \alpha_1 + d_2 \cos(\alpha_1 + \alpha_2) \)
- \( y = d_1 \sin \alpha_1 + d_2 \sin(\alpha_1 + \alpha_2) \)

Example Obstacles in C-Space
Two-link manipulator

- Demo
  
  http://www-inst.eecs.berkeley.edu/~cs188/fa08/demos/robot.html

Probabilistic Roadmaps

- Idea: sample random points as nodes in a visibility graph
- This gives probabilistic roadmaps
  - Very successful in practice
  - Lets you add points where you need them
  - If insufficient points, incomplete or weird paths

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Perception

1. Find a point see in two camera views
2. Find 3D coordinates by finding the intersection of the rays

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Motivating Example

- How do we specify a task like this?

[Demo: autorotate / tictoc]

Autonomous Helicopter Flight

- Key challenges:
  - Track helicopter position and orientation during flight
  - Decide on control inputs to send to helicopter
Autonomous Helicopter Setup

- On-board inertial measurement unit (IMU)
- Send out controls to helicopter

HMM for Tracking the Helicopter

- State: \( s = (x, y, z, \phi, \theta, \psi, \dot{x}, \dot{y}, \dot{z}, \dot{\phi}, \dot{\theta}, \dot{\psi}) \)
- Measurements:
  - 3-D coordinates from vision, 3-axis magnetometer, 3-axis gyro, 3-axis accelerometer
- Transitions (dynamics): [time elapse update]
  - \( s_{t+1} = f(s_t, a_t) + w_t \)
    - \( f \) encodes helicopter dynamics
    - \( w \) is a probabilistic noise model

Helicopter MDP

- **State:** \( s = (x, y, z, \phi, \theta, \psi, \dot{x}, \dot{y}, \dot{z}, \dot{\phi}, \dot{\theta}, \dot{\psi}) \)

  **Actions (control inputs):**
  - \( a_\text{lon} \): Main rotor longitudinal cyclic pitch control (affects pitch rate)
  - \( a_\text{lat} \): Main rotor latitudinal cyclic pitch control (affects roll rate)
  - \( a_\text{col} \): Main rotor collective pitch (affects main rotor thrust)
  - \( a_\text{rud} \): Tail rotor collective pitch (affects tail rotor thrust)

  **Transitions (dynamics):**
  - \( s_{t+1} = f(s_t, a_t) + w_t \)
    - \( f \) encodes helicopter dynamics
    - \( w \) is a probabilistic noise model

  - Can we solve the MDP yet?

Problem: What’s the Reward?

- Rewards for hovering:
  - \( R(s) = -\alpha_x (x - x^*)^2 + \alpha_y (y - y^*)^2 + \alpha_z (z - z^*)^2 \)
  - \( + \alpha_x (\dot{x} - \dot{x}^*)^2 + \alpha_y (\dot{y} - \dot{y}^*)^2 + \alpha_z (\dot{z} - \dot{z}^*)^2 \)

- Rewards for “Tic-Toc”?
  - Problem: what’s the target trajectory?
  - Just write it down by hand?

Helicopter Apprenticeship?

- Intended trajectory satisfies dynamics.
- Expert trajectory is a noisy observation of one of the hidden states.
- But we don’t know exactly which one.

Probabilistic Alignment using a Bayes’ Net

- Intended trajectory
  - \( s_{t+1} = f(s_t) + \omega_t \)
  - \( \omega_t \) represents sensor noise

- Expert demonstrations
  - \( y_j = z_{ij} + \nu_j \)
  - \( \nu_j \) represents expert noise

- Time indices

[Coates, Abbeel & Ng, 2008]
Alignment of Samples

- Result: inferred sequence is much cleaner!

Final Behavior

Advanced Applications

- Low-level control problem: moving a foot into a new location → similar search as for moving robot arm
- High-level control problem: where should we place the feet?
  - Reward function $R(x) = w \cdot f(s)$  [25 features]

Quadruped

Apprenticeship Learning

- Goal: learn reward function from expert demonstration
- Assume $R(s) = w \cdot f(s)$
- Get expert demonstrations $s = (s_0, s_1, \ldots, s_n)$
- Guess initial policy $\pi_0$
- Repeat:
  - Find $w$ which make the expert better than $\{\pi_0, \pi_1, \ldots, \pi_{i-1}\}$
    $w_i \leftarrow$ distinguish $\{\pi^*, \{\pi_0, \pi_1, \ldots, \pi_{i-1}\}\}$
  - Solve MDP for new weights $w_i$:
    $\pi_i \leftarrow$ solve $\text{MDP}(w_i)$
Advanced Applications

Autonomous Vehicles

Grand Challenge: Barstow, CA, to Primm, NV

150 mile off-road robot race across the Mojave desert
Natural and manmade hazards
No driver, no remote control
No dynamic passing

Inside an Autonomous Car

Readings: No Obstacles
Obstacle Detection

Trigger if \(|Z_i - Z_j| > 15\text{cm}\) for nearby \(z_i, z_j\)

Readings: Obstacles

Probabilistic Error Model

HMMs for Detection

Raw Measurements: 12.6% false positives

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HMM Inference: 0.02\% false positives