# 236609 - AI and Robotics - Fall 2022

## Lesson 3: A slightly deeper dive into the three decision-making layers

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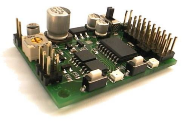
# Components of a Robotic Agents



**Sensors**

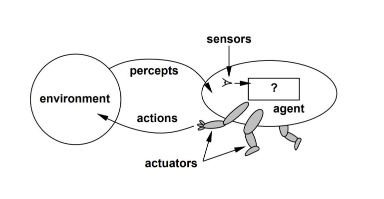

**Controllers**



**Actuators**

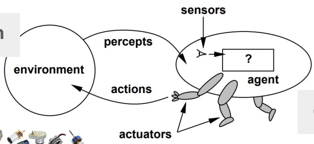
# Autonomy

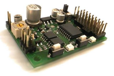




# Autonomy

state estimation



decision making

motion control

# Autonomy

### State Estimation

$$\beta : \mathcal{S} \mapsto [0, 1]$$

Process incoming observations to maintain a *belief* as a probability distribution over states

### Decision Making

$$\pi : \beta \mapsto \mathcal{A}$$
$$\pi : \beta \times \mathcal{A} \mapsto [0, 1]$$

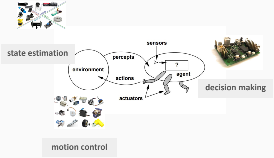
Find a policy - a mapping belief and objective into actions (probabilities)

### Motion Control

$$\dot{x}(t) = f(x(t), u(t), t) + w(t)$$

Translate actions into low-level commands (and monitor their execution)

- $x(t) \in \mathbb{R}^n$ - state vector
- $u(t) \in \mathbb{R}^m$ - control input
- $f : \mathbb{R}^n \times \mathbb{R}^m \times \mathbb{R} \to \mathbb{R}^n$ - system dynamics
- $w(t)$ - noise or disturbance



# Layered Control Architecture (LCA)

| | | |
|---|---|---|
| Semantic Logic<br>Discrete Planning | **Decision Making** | Flexible<br>and Slow |
| Optimization<br>Sampling Methods<br>Continuous Planning | **Trajectory Planning** | Intermediate |
| PID Control<br>CLFs/CBFs | **Feedback Control** | Rigid and<br>Real Time |

# Information Flow





**Top-Down Flow:**

- Goals → Plans → Commands
- Like company policies becoming specific actions

**Bottom-Up Flow:**

- Sensor data → Status updates → Results
- Like workers reporting to management

# Time Scales



Different Speeds for Different Needs

- Planning: Seconds to minutes
- Behavioral: Fraction of seconds
- Execution: Milliseconds
- Control: Microseconds
- Hardware: Nanoseconds

# Layered Control Architecture (LCA)



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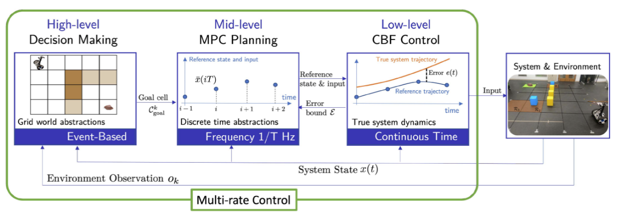
Matni, Nikolai, Aaron D. Ames, and John C. Doyle. ”A Quantitative Framework for Layered Multirate Control: Toward a Theory of Control Architecture.” IEEE Control Systems Magazine (2024)

# Layered Control Architecture (LCA)






Matni, Nikolai, Aaron D. Ames, and John C. Doyle. "A Quantitative Framework for Layered Multirate Control: Toward a Theory of Control Architecture." IEEE Control Systems Magazine (2024)

# Why Do We Need Layered Control?



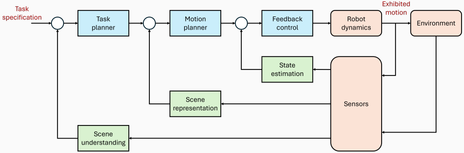
**Challenge:** Robots need to:

- Make high-level decisions
- React to their environment
- Control precise movements
- Handle multiple tasks
- Respond at different speeds

# The Three Layers

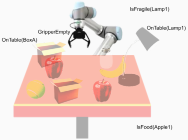
# Layered Control Architecture (LCA)






# Task Planning

# Top Layer: High level planning




**Example:**

- Realize that the human needs a food item.
- Reason about the reachability of items and the ability to perceive them.
- Decide which food object to pick-up.
- Optional - Prepare for failure via a contingent plan
- ...

What is a good model?

# Markov Decision Process

A **Markov Decision Process**(MDP) is a tuple $\langle \mathcal{S}, \mathcal{A}, \mathcal{P}, \mathcal{R}, \gamma \rangle$ where

- $\mathcal{S}$ is a finite set of states
- $\mathcal{A}$ is a finite set of actions
- $\mathcal{P}$ is a state transition probability matrix
  $\mathcal{P}^a_{s,s'} = \mathcal{P}[S_{t+1} = s' | S_t = s, A_t = a]$
- $\mathcal{R}$ is a reward function, $\mathcal{R}^a_s = \mathbb{E}[R_{t+1} | S_t = s, A_t = a]$, and
- **optional:** $\gamma$ is a discount factor $\gamma \in [0, 1]$ that is used to favor immediate rewards over future rewards.

The Markov property: "The future is independent of the past given the present".

Extensions: Infinite and continuous MDPs, partially observable MDPs, undiscounted, average reward MDPs. etc.

# Partially Observable Markov Decision Process (POMDP)



A **Partially Observable Markov Decision Process**(POMDP) is a tuple $\langle \mathcal{S}, \mathcal{A}, \mathcal{P}, \mathcal{R}, \gamma, \Omega, \mathcal{O}, \beta_0 \rangle$ where

- $\mathcal{S}$, $\mathcal{A}$, $\mathcal{P}$, $\mathcal{R}$ and $\gamma$ are as for an MDP.
- $\Omega$ is a set of observations (observation tokens),
- $\mathcal{O}$ is a sensor function specifying the conditional observation probabilities $\mathcal{O}^o_{s,a} = \mathcal{P}[O_{t+1} = o | S_t = s, A_t = a]$ of receiving observation token $o \in \Omega$ in state $s$ after applying action $a$ [1].
- $\beta_0$ the initial belief: a probability distribution over the states such that $\beta_0(s)$ stands for the probability of $s$ being the true initial state.

[1] alternatively: $\mathcal{O}^o_s = \mathcal{P}[o_t = o | S_t = s]$

# Partially Observable Markov Decision Process (POMDP)



In its most general formulation, a belief $\beta$ is represented as a probability distribution over the states $\mathcal{S}$, such that $\beta(s)$ stands for the probability of $s$ being the true state.

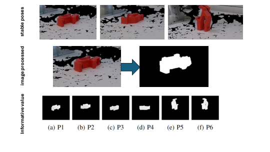



**Figure 1:** How to represent beliefs of robotic agents?

Typically, each agent is associated with a **belief update function** $\tau : \mathcal{B} \times \Omega \mapsto \mathcal{B}$ that represents how a belief changes when receiving a new observation.

# POMDP for our example?

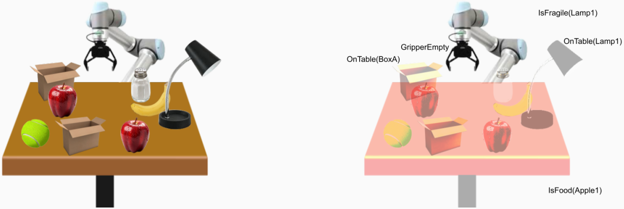



**Figure 2:** What is a good representation ?

# YAY! POMDPs



- The POMDP provides a principled and formal framework for long-term decision making in settings in which it is important to account for the probabilistic nature of the sensor function.
- Has been successfully used in many robotic applications, including localization and navigation, search and tracking, autonomous driving, multi-robot systems, manipulation, and human-robot interaction.
- A key benefit: many planning tools that have been developed (most based on sampling and approximations).

# POMDPs are hard! (and not always needed)



- Need to address the continuous nature of the environment through approximation and discretization techniques or through specialized algorithms designed for continuous domains.
- Computationally intractable - especially true for the high-dimentional robotic settings.

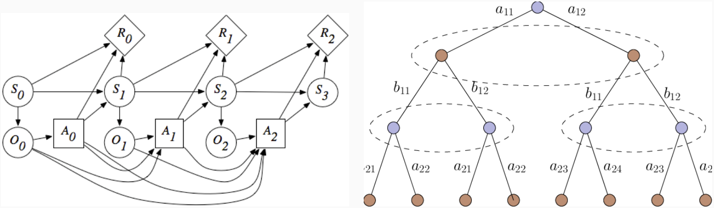



**Figure 3:** POMDP planning

## Ideas?

# Solution Approaches



- Use a simpler model when possible (e.g., MDP)
- Function approximations (AKA as Deep Learning)
- Sampling based approaches.
- Adopt a modular approach that decomposes the system into modules for state estimation, planning, and control

More on this later in the course !

# Motion Planning

- Task planning focuses on achieving high-level goals and on finding sequences of high-level actions to achieve them
- Motion planning ensures the physical feasibility of these actions by generating **collision-free paths** or trajectories that respect the robot's **kinematic and dynamic constraints**.

Happens in a high-dimensional space!

From **Oren Salzman's** course slides*

**(Formal) definition of the basic motion-planning** problem**
Let $\mathcal{R}$ be a robot system with $d$ **degrees of freedom**, moving in a known environment cluttered with obstacles. Given start and target **configurations** $q_0$ and $q_g$ for $\mathcal{R}$, decide whether there is a collision-free, continuous path $\tau : [0, 1] \rightarrow \mathcal{C}_{free}$ such that $\tau(0) = q_0$ and $\tau(1) = q_g$ and if so, plan such a motion.

---

Alternatively, we can consider a *motion path* from initial configuration $q_0 \in \mathcal{C}$ to goal configuration $q_g \in \mathcal{C}$ as a sequence of configurations $(q_0, q_1, ..., q_m = q_0)$ where for all $i$, $\{\alpha q_{i-1} + (1 - \alpha)q_i | \alpha \in [0, 1]\} \subseteq \mathcal{C}_{free}$.

*Consider taking course 236901 to learn about algorithms for robotic motion planning.

https://arxiv.org/pdf/2209.14471.pdf

# Motion Planning for our example?



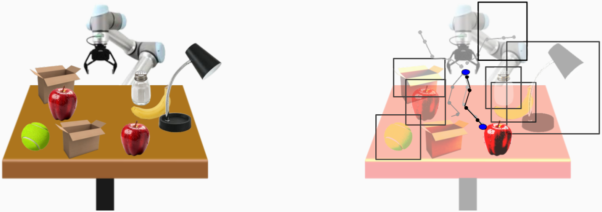


**Figure 4:** What is a good representation ?

Happens in a high-dimensional space!

# Motion Planning

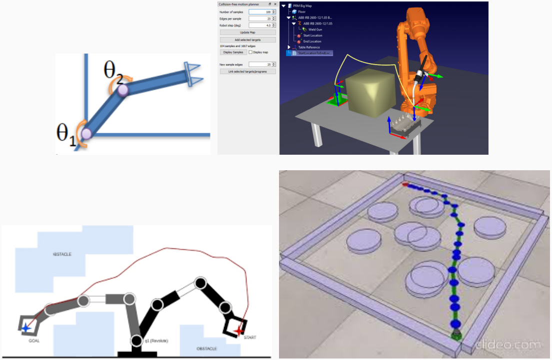



**Figure 5:** Motion Planning Examples

Happens in a high-dimensional space!

- Typically, in order to support computationally feasibility, the path that the motion planner generates is a discretized abstraction of a path
- A path $\tau = \{w_i\}_{i=0}^{N}$ is is a sequence of waypoints $w_i$, where $N$ denotes the total number of waypoints in $\tau$, and $w_0$ and $w_N$ represent the initial and goal configurations $q_0$ and $q_g$, respectively.

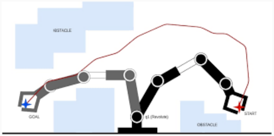
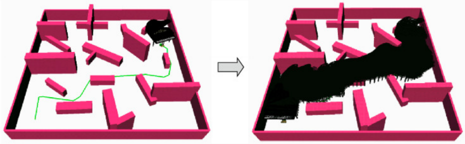



**Figure 6:** Motion Planning

# Motion Planning is Hard





Motion planning approaches are diverse: optimization-based methods (e.g., trajectory optimization, gradient descent) sampling-based methods (e.g., Rapidly-exploring Random Trees (RRT) and Probabilistic Roadmaps (PRM)), physics-based planners and hybrid approaches.

More on this later on ...

# Feedback Control - Motion Control

# Feedback Control



- Once a motion plan is found, there is a need to execute it.
- While motion planning aims to find the best path for the robot to follow,
- focus on ensuring that the robot follows this trajectory in the presence of real-world factors like sensor noise, dynamic disturbances, or actuator inaccuracies.

# Feedback Control for our example?

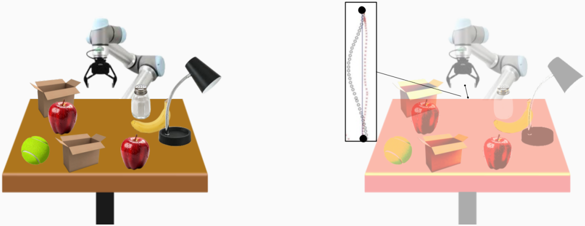
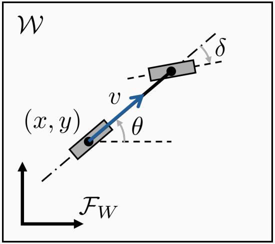
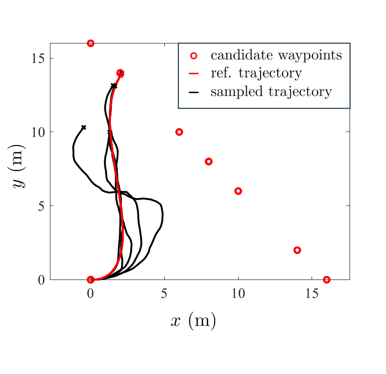


Figure 7: What is a good representation ?

Happens in a high-dimensional space!

# Feedback Control



# Feedback Control

- To describe the control episode between consecutive waypoints $w_{j-1}$ and $w_j$ denoted by $\gamma_j$, we use a *dynamic model*.
- Let $\mathcal{F}_{\mathcal{W}}$ denote the inertial frame of reference embedded in $\mathcal{W}$, with origin $\mathcal{O}_{\mathcal{W}}$. The state $\mathbf{x}(k) \in \mathcal{R} \subset \mathbb{R}^d$ of the mobile agent is governed by the following difference equation,

$$\mathbf{x}(k+1) = f[\mathbf{x}(k) + \mathbf{B}[\mathbf{x}(k)]\mathbf{u}(k) + \mathbf{p}(k) \quad (1)$$

  where $k = 0, \cdots, T$ is the index of time steps in the control episode, $\mathbf{u}(k) \in \mathcal{U} \subset \mathbb{R}^m$ is the control input, $\mathbf{B}[\mathbf{x}(k)]$ is the control effect matrix, and the vector $\mathbf{p}(k)$ represents process noise.
- We refer to the deterministic system with $\mathbf{p}(k) \equiv 0$ as the nominal model.

# Feedback Control



- Given the dynamic model, the challenge is to design a control system to set the behavior of a dynamic system in a desired way.
- This involves determining a sequence of control inputs $\mathbf{u}(k)$ to achieve specified states while satisfying system constraints, and dynamically adjusting them based on the current state.
- Many model-based approaches (e.g., PID, LQR, MPC) and many emerging techniques based on neural network-based control.

# Putting it All Together

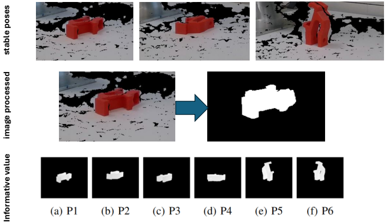
# 3-tiered State Estimation

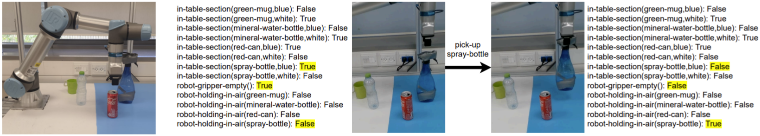


- The account so far considers external or internal factors that affect the system dynamics but are not directly controlled or predicted by the model.
- In some settings, it is beneficial to explicitly model sensor noise, and the mapping between states and observations.
- State estimation needs to be performed for the 3 layers of abstraction:
  - What is the value of POMDP features ?
  - What is the position of the robot w.r.t its motion plan?
  - What is the position of the robot w.r.t its nominal path to the next waypoint?

# State Estimation at the CLAIR Lab






(a) Setup. (b) Example transition annotated with S3E. State changes highlighted.

# 3-tiered State Estimation



For task planning, we have a probabilistic sensor function where $\Omega$ is a set of observations and $\mathcal{O}$ is a sensor function specifying the conditional observation probabilities $\mathcal{O}^{o}_{s,a} = \mathcal{P}[O_{t+1} = o | S_t = s, A_t = a]$ of receiving observation token $o \in \Omega$ in state $s$ after applying action $a$ .

At the lower levels, a *sensor function* is used to record the position of the mobile agent in the inertial frame $\mathcal{F}_{\mathcal{W}}$ as

$$\mathbf{z}(k) = h[\psi(k)] + \mathbf{q}(k). \tag{2}$$

where, $h$ is the expected observation of the system state $\psi(k)$ and $\mathbf{q}(k) \sim \mathcal{N}(\mathbf{0}, \mathbf{R})$ is the zero-mean i.i.d. Gaussian sensor noise.

# Putting it all Together

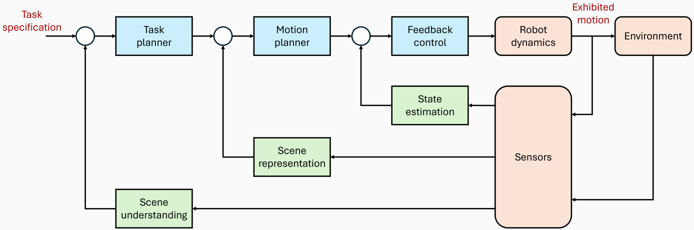



Figure 9: Full Process

# Putting it all Together

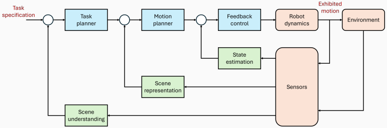



**Figure 10:** Caption

## Different Time Scales for Different Needs

- Planning: Seconds to minutes
- Behavioral: Fraction of seconds
- Execution: Milliseconds
- Control: Microseconds
- Hardware: Nanoseconds

## Information Flow:

- **Top-Down Flow:** Goals → Plans → Commands
- **Bottom-Up Flow:** Sensor data → Status updates → Results

## Any ideas for information flow?

# Summary



Summary:

- We looked at the different layers of decision-making

What next ?

- Take a closer look at feedback control