

**Caltech**

# A Multi-Layer Approach to Safety-Critical Dynamic CPS

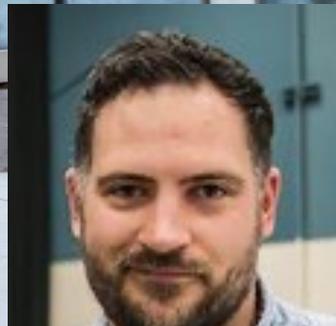
*Ugo Rosolia*

*Postdoctoral scholar*

*Mechanical and Civil Engineering*

*Control and Dynamical Systems*

*California Institute of Technology*



**Prof. A. D. Ames**  
Caltech

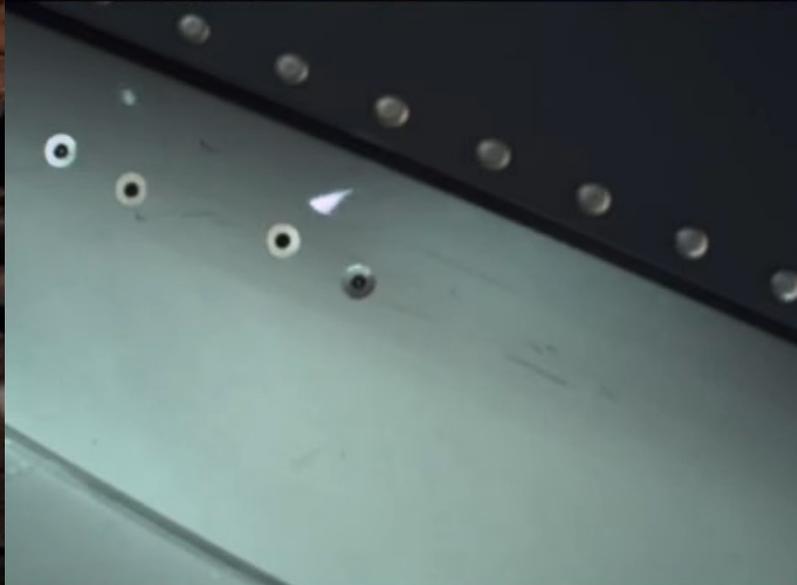


**Dr. M. Ahmadi**  
Caltech



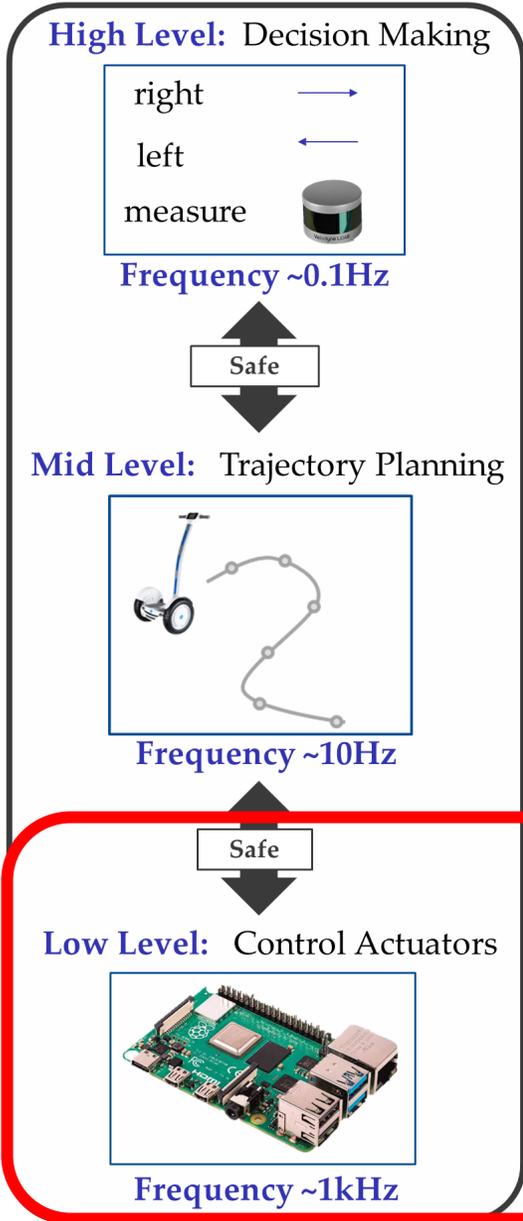
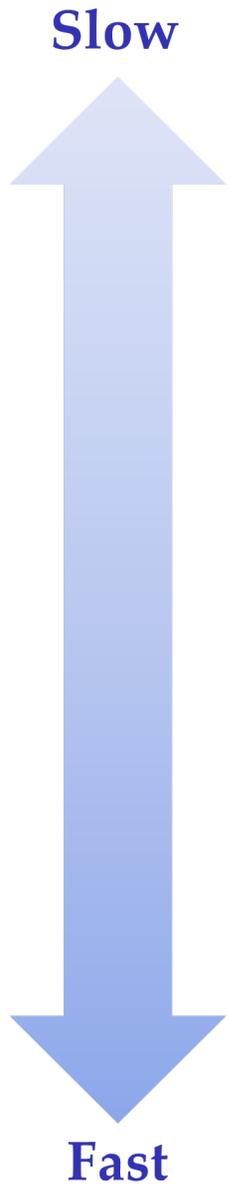
**A. Singletary**  
Caltech

# Application: Space Exploration



Guaranteeing Safe Autonomy?

# Multi-Agent Autonomy



*POMDP planning*

*Model Predictive Control*

*Control Barrier Functions*



# Low-level Controllers - Bipedals

## Lyapunov Controller

$$u^*(x) = \underset{(u, \delta) \in U \times \mathbb{R}}{\operatorname{argmin}} \|u - u_{\text{des}}(x)\|^2$$

s.t.  $\dot{V}(x, u) \leq -\alpha V(x)$

+ Theorem  $\Rightarrow$  Stable Walking

Low Level: Control Actuators



Frequency  $\sim 1\text{kHz}$

# Low-level Controllers - Quadrupeds

## Lyapunov Controller

$$u^*(x) = \underset{(u, \delta) \in U \times \mathbb{R}}{\operatorname{argmin}} \quad \|u - u_{\text{des}}(x)\|^2$$

s.t.  $\dot{V}(x, u) \leq -\alpha V(x)$

+ Theorem  $\Rightarrow$  Stable Walking



Low Level: Control Actuators



Frequency  $\sim 1\text{kHz}$

Ma, AA, ICRA 2020, CSL 2020

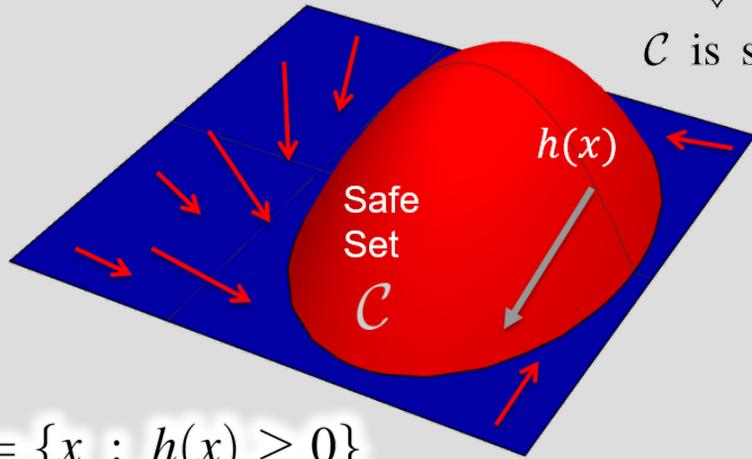
Ma, Csomay-Shanklin, AA, RAL/ICRA 2021 (to appear)

Control barrier functions

$$\dot{h}(x, u) \geq -\gamma h(x)$$



$\mathcal{C}$  is safe



$$\mathcal{C} = \{x : h(x) \geq 0\}$$

Control Barrier Functions

Provide a framework for safety-critical control:  
Necessary and sufficient conditions for set invariance

- **Dynamics:**  $\dot{x} = f(x) + g(x)u$
- **Safe set  $\mathcal{C}$ :** defined by  $h$ :

$$\mathcal{C} = \{x \in \mathbb{R}^n : h(x) \geq 0\}$$

Ames, Tabuada Grizzle (2014)

Almost definit of Barrier function:  
 $B(x) > 0 \iff x \in \text{Int}(\mathcal{C})$   
 $\dot{B} \geq -\alpha(B)$   
 where  $\alpha$  is a class  $\mathcal{K}$  function

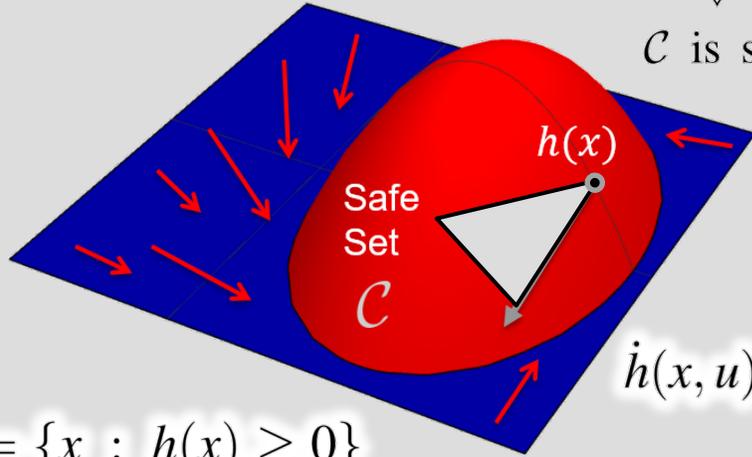


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 $B(x) > 0 \iff x \in \text{Int}(\mathcal{C})$   
 $\dot{B} \geq -\alpha(B)$   
 ch  $\alpha$  is a class  $\mathcal{K}$  function

Control Barrier Function

For all  $x \in \mathcal{C}$ , there exists  $u \in \mathbb{R}^m$  such that:

$$\dot{h}(x, u) = \frac{\partial h}{\partial x}(x)(f(x) + g(x)u) \geq -\gamma(h(x))$$



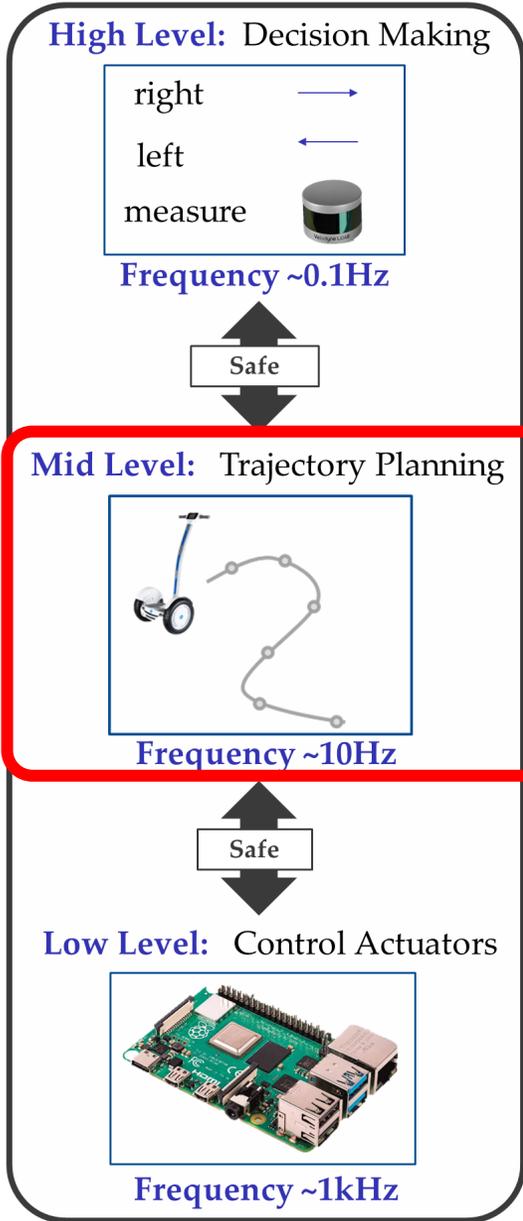
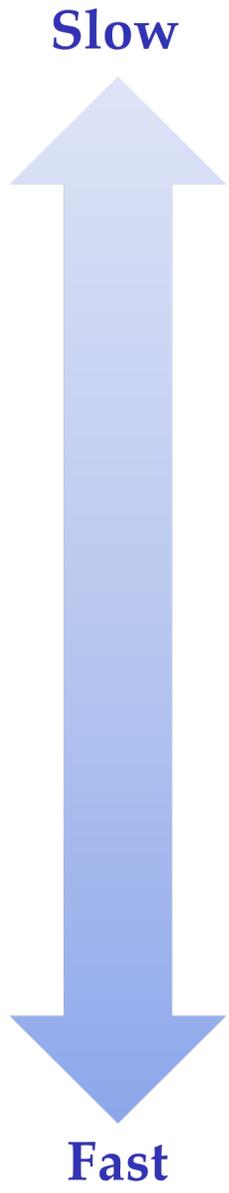
$\mathcal{C}$  is safe

AA, Tabuada Grizzle, CDC 2014

AA, Xu, Tabuada Grizzle, TAC 2017

Here  $\gamma : \mathbb{R} \rightarrow \mathbb{R}$  is an extended class  $\mathcal{K}$  function (strictly increasing with  $\gamma(0) = 0$ ).

# Multi-Agent Autonomy



*POMDP planning*



*Model Predictive Control*



*Control Barrier Functions*



**Mid Level:** Trajectory Planning



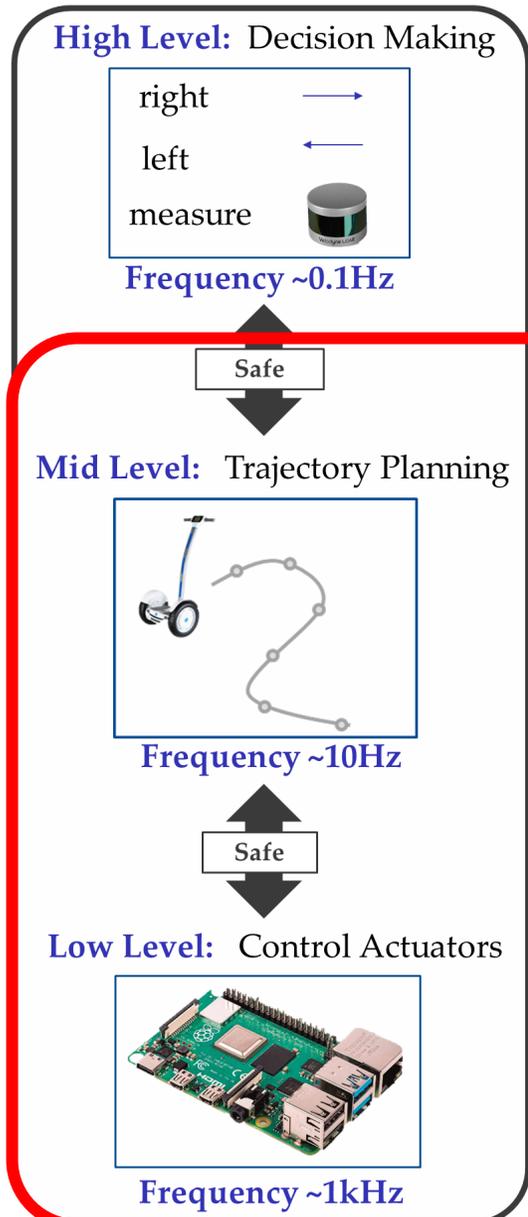
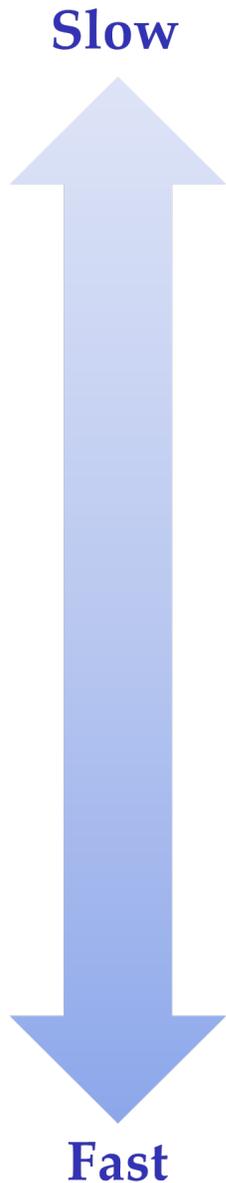
Frequency ~10Hz

**Learning MPC**

$$\begin{aligned} \min_{u_0, \dots, u_{N-1}} \quad & \sum_{t=0}^N l(x_t, u_t) + Q^j(x_N) \\ \text{s.t.} \quad & x_{k+1} = A_k x_k + B_k u_k + w_k \\ & x_k \in \mathcal{X}, u_k \in \mathcal{U}, x_N \in \mathcal{CS}^j \\ & x_0 = x(t), \forall w_k \in \mathcal{W} \end{aligned}$$

**+ Theorem  $\Rightarrow$  Optimality**

# Multi-Agent Autonomy



*Model Predictive Control*

*Control Barrier Functions*

## Robust MPC

$$\min_{u_0, \dots, u_{N-1}} \sum_{t=0}^N l(x_t, u_t) + Q(x_N)$$

Linearized model

$$\text{s.t. } x_{k+1} = A_k x_k + B_k u_k + w_k$$
$$x_k \in \mathcal{X}, u_k \in \mathcal{U}, \forall w_k \in \mathcal{W}$$
$$x_0 = x(t)$$

Model errors

## CBF safe tracking

From MPC

$$u^*(x) = \operatorname{argmin}_{(u, \delta) \in U \times \mathbb{R}} \|u - u_{\text{des}}(x)\|^2$$
$$\text{s.t. } \dot{h}(x, u) \geq -\alpha(h(x))$$

Guarantees tracking error bounds

**Property (low level safety).** The control policy  $\pi^u(\cdot)$  from the augmented system guarantees low level safety for the closed-loop system, if there exists a set  $\mathcal{S}_x \subseteq \mathcal{X}_c$  such that  $\forall x^+(t_k) \in \mathcal{S}_x \cap \mathcal{X}_d$  and  $\forall v^+(t_k) \in \mathcal{V}$  we have that

$$x(t) \in \mathcal{S}_x \text{ and } u(t) \in \mathcal{U}, \forall t \in (t_k, t_{k+1}].$$

**Property (low level tracking).** The control policy  $\pi^u(\cdot)$  from the augmented system guarantees low level tracking for the closed-loop augmented system, if there exists a set  $\mathcal{S}_e$  such that  $\forall e^+(t_k) = x^+(t_k) - \bar{x}^+(t_k) \in \mathcal{S}_e, \forall x^+(t_k) \in \mathcal{S}_x \cap \mathcal{X}_d$  and  $\forall v^+(t_k) \in \mathcal{V}$  we have that

$$e(t) = x(t) - \bar{x}(t) \in \mathcal{S}_e, \forall t \in (t_k, t_{k+1}].$$

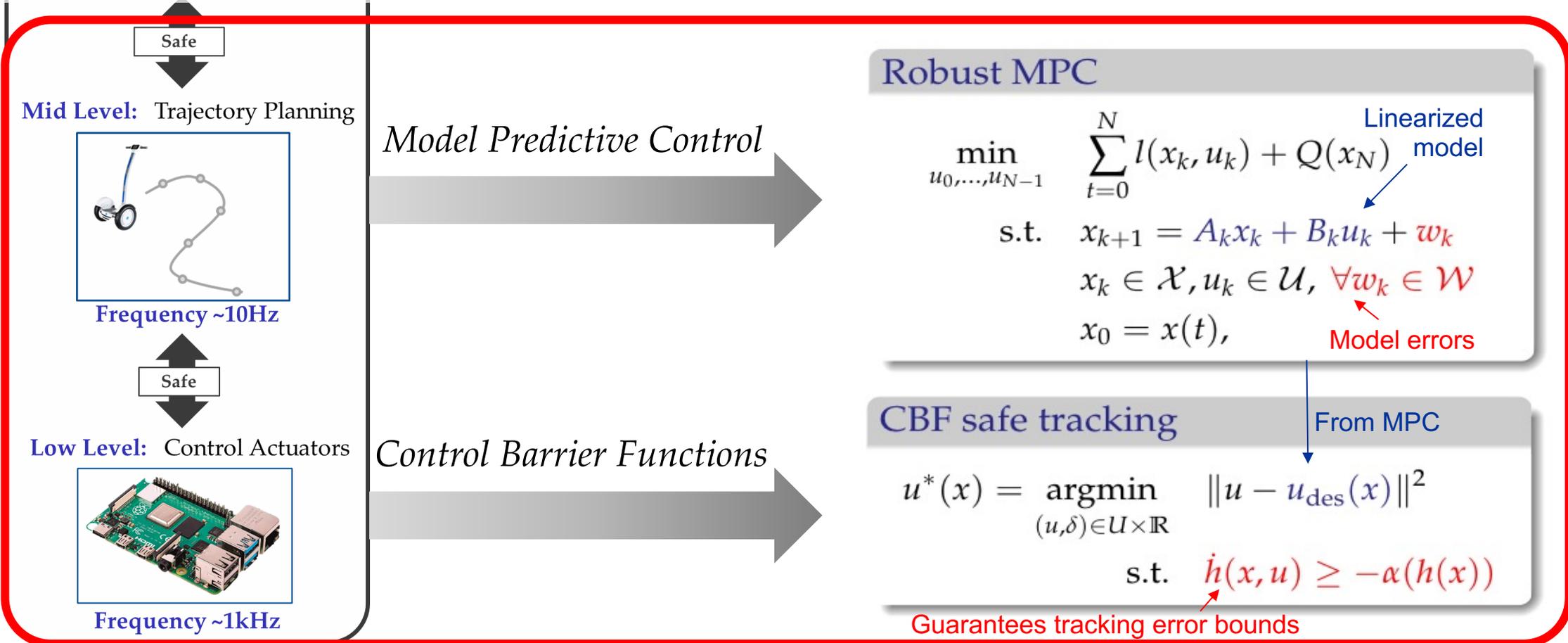
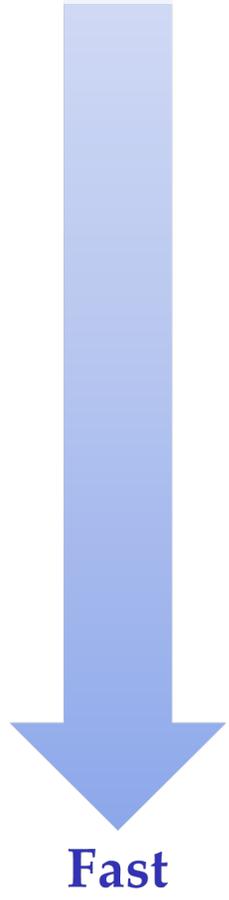
**Contracts on Operating Conditions**

**Property (mid level safety).** The control policy  $\pi^v(\cdot)$  guarantees high level safety for the augmented closed-loop system, if for the initial conditions  $x(0) = \bar{x}(0) + e(0) \in \mathcal{S}_x \cap \mathcal{X}_d$  and  $e(0) \in \mathcal{S}_e$  we have that

$$z \in \mathcal{S}_x \cap \mathcal{X}_d, \\ \pi^v(z) \in \mathcal{V}, \forall z \in \Delta(\bar{x}^-(t_k) \oplus \mathcal{S}_e), \forall k \in \{0, 1, \dots\}.$$

**Contracts on Tracking bounds**

**Property (mid level tracking).** The reset map  $\Delta_e(\cdot)$  from the augmented system guarantee high level tracking for the augmented closed-loop system, if for the initial conditions  $x(0) = \bar{x}(0) + e(0) \in \mathcal{S}_x \cap \mathcal{X}_d$  and  $e(0) \in \mathcal{S}_e$  we have that

$$\Delta(z) = \Delta_{\bar{x}}(z) + \Delta_e(z), \\ \Delta_e(z) \in \mathcal{S}_e, \forall z \in \bar{x}^-(t_k) \oplus \mathcal{S}_e, \forall k \in \{0, 1, \dots\}.$$


**Robust MPC**

$$\min_{u_0, \dots, u_{N-1}} \sum_{t=0}^N l(x_t, u_t) + Q(x_N) \quad \text{Linearized model}$$

$$\text{s.t. } x_{k+1} = A_k x_k + B_k u_k + w_k$$

$$x_k \in \mathcal{X}, u_k \in \mathcal{U}, \forall w_k \in \mathcal{W}$$

$$x_0 = x(t), \quad \text{Model errors}$$

**CBF safe tracking**

$$u^*(x) = \operatorname{argmin}_{(u, \delta) \in \mathcal{U} \times \mathbb{R}} \|u - u_{\text{des}}(x)\|^2$$

$$\text{s.t. } \dot{h}(x, u) \geq -\alpha(h(x))$$

Guarantees tracking error bounds

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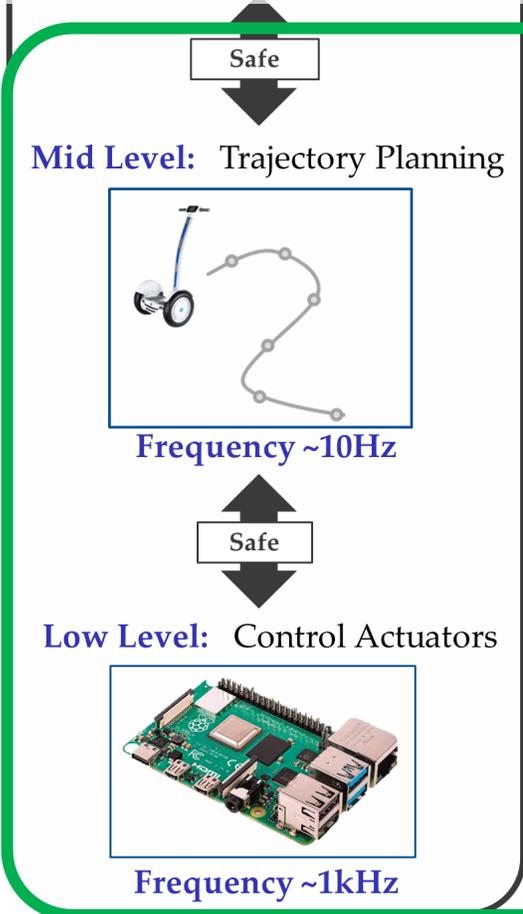
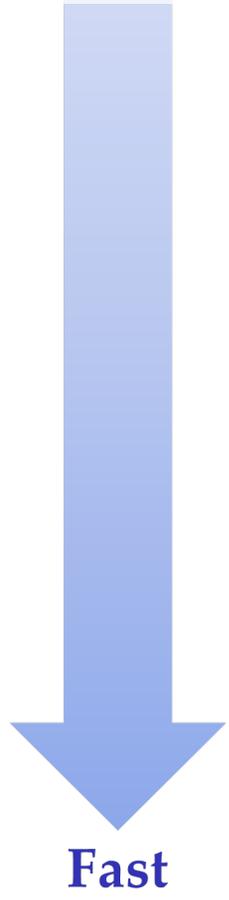
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*Model Predictive Control*

**Safe Interconnection**

*Control Barrier Functions*

**Robust MPC**

$$\min_{u_0, \dots, u_{N-1}} \sum_{t=0}^N l(x_k, u_k) + Q(x_N) \quad \text{Linearized model}$$

s.t.  $x_{k+1} = A_k x_k + B_k u_k + w_k$   
 $x_k \in \mathcal{X}, u_k \in \mathcal{U}, \forall w_k \in \mathcal{W}$  (Model errors)  
 $x_0 = x(t)$

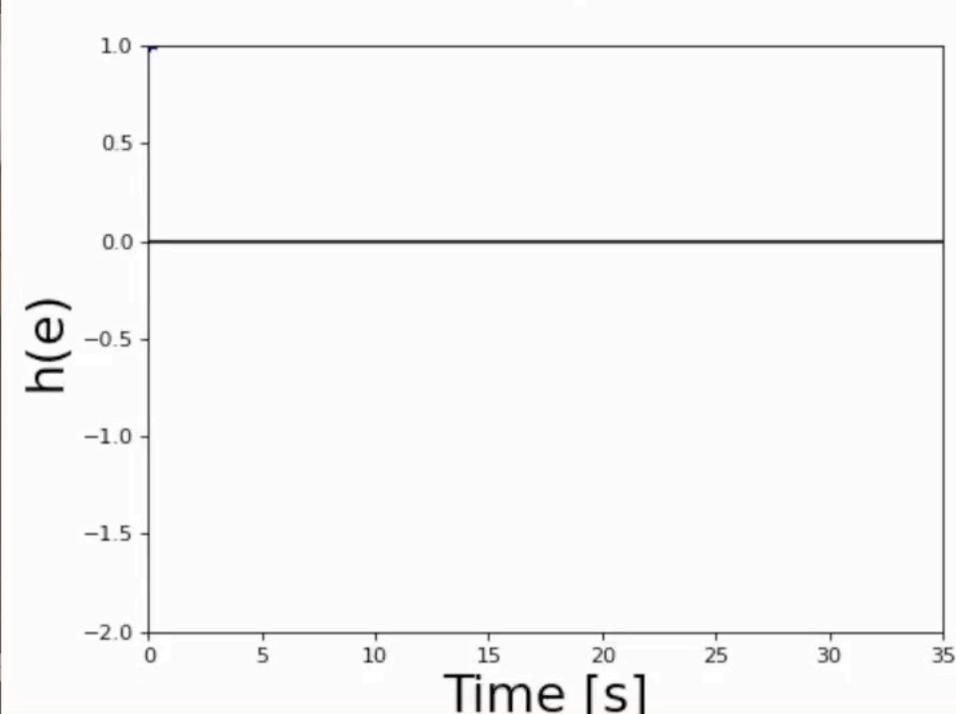
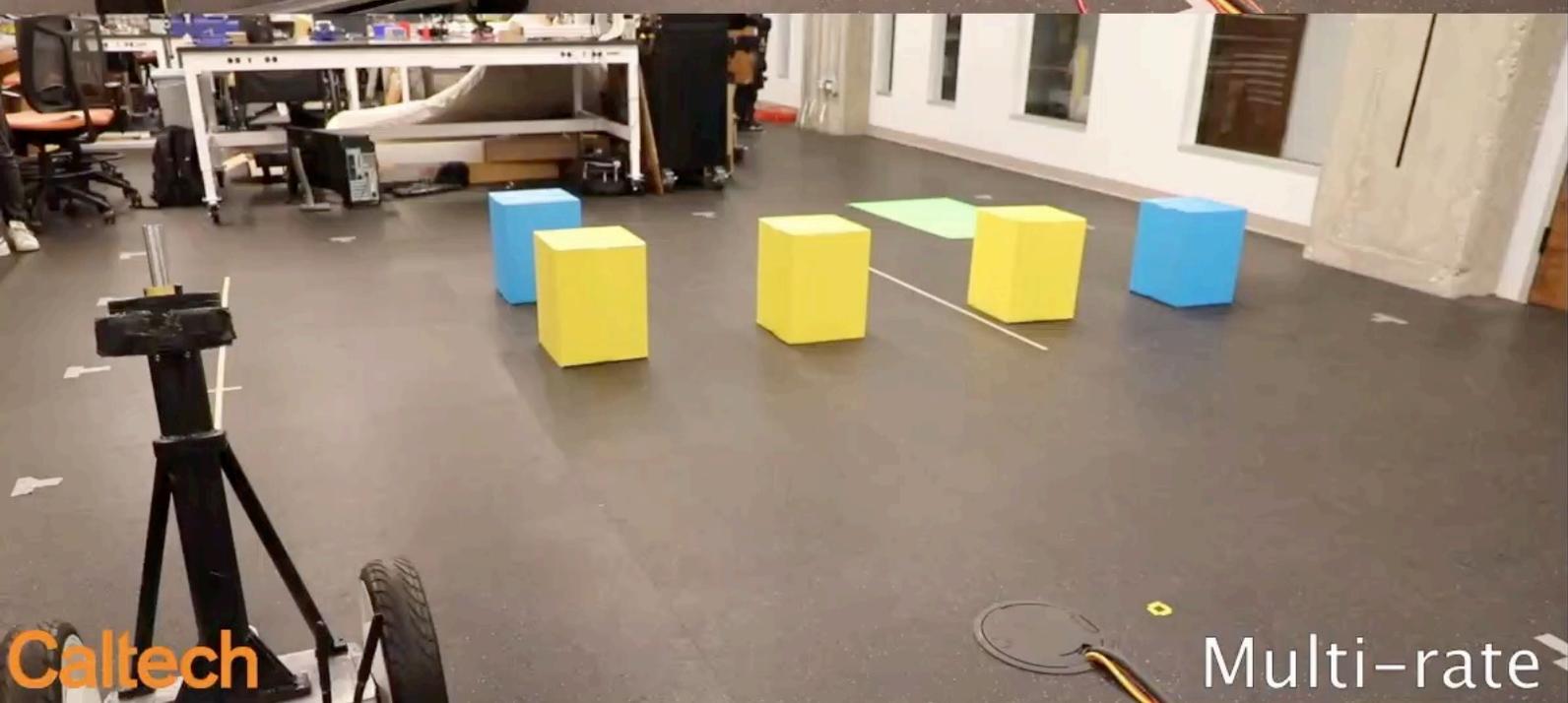
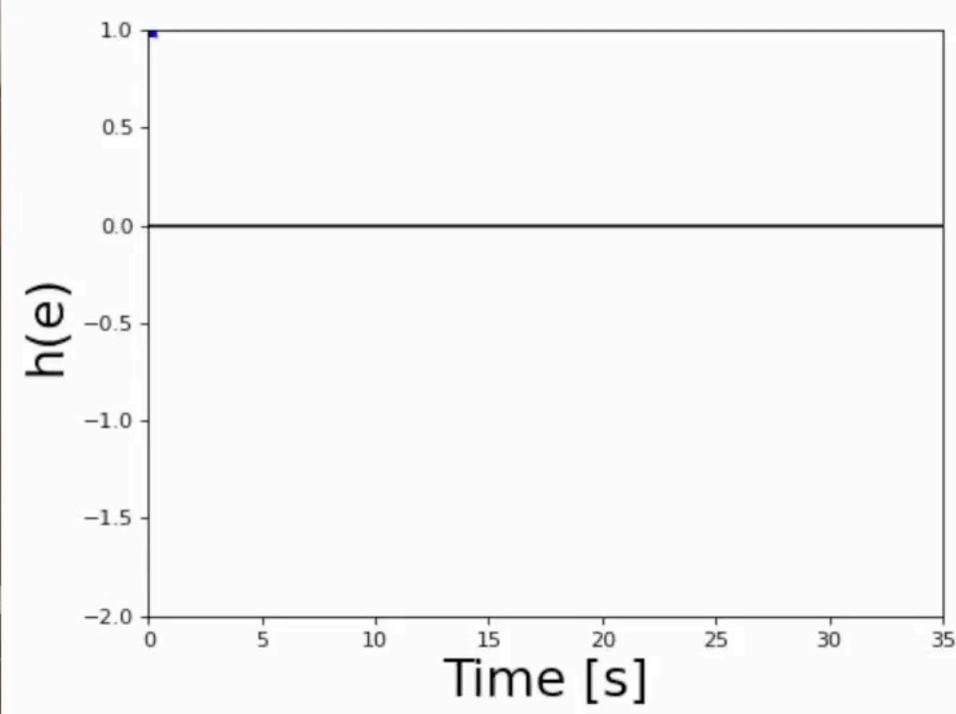
**CBF safe tracking**

$$u^*(x) = \operatorname{argmin}_{(u, \delta) \in \mathcal{U} \times \mathbb{R}} \|u - u_{\text{des}}(x)\|^2$$

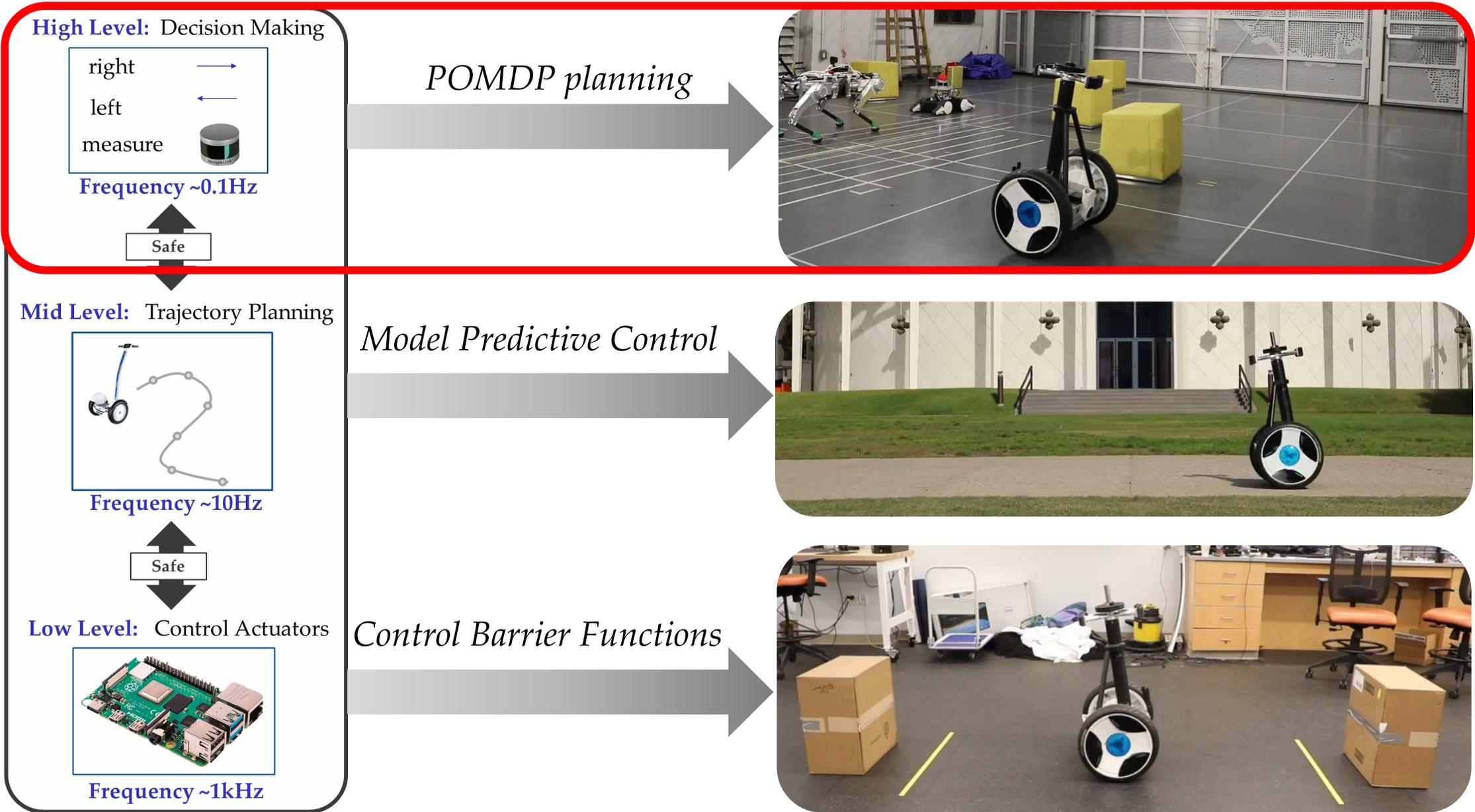
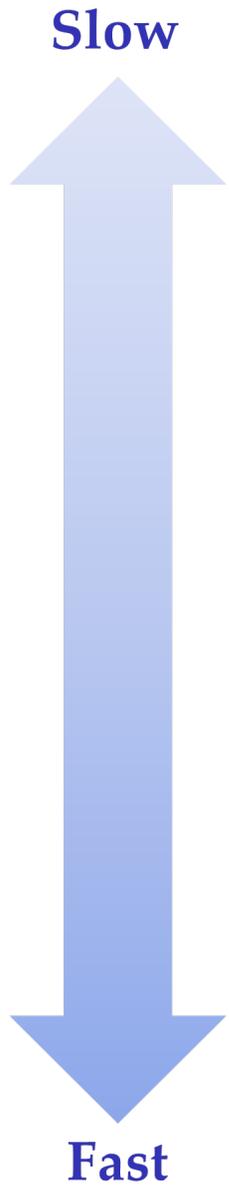
s.t.  $\dot{h}(x, u) \geq -\alpha(h(x))$

Guarantees tracking error bounds

# Comparison with a Naïve MPC



# Multi-Agent Autonomy



The mission objective is to find the science sample given partial environment observations

Science sample



Uncertain Region

$\mathcal{R}_1$

Known Obstacles



POMDP Planning

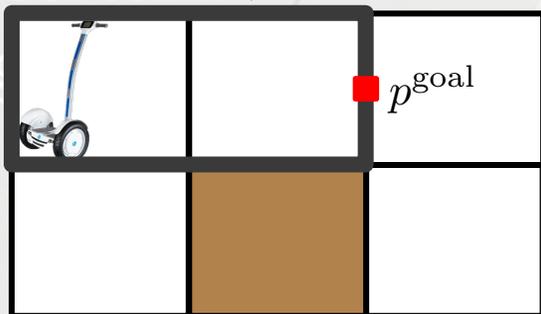
Minimize time to completion

$$\mu^s = \operatorname{argmin}_{\mu} \mathbb{E}^{\mu} \left[ \sum_{k=0}^N \mathbb{1}_{\mathcal{G}}(s_k^r) \right]$$

s.t.  $\mu \in \operatorname{argmax}_{\kappa} \mathbb{P}^{\kappa}[\omega^r \models \psi^r]$

Maximize probability of being safe

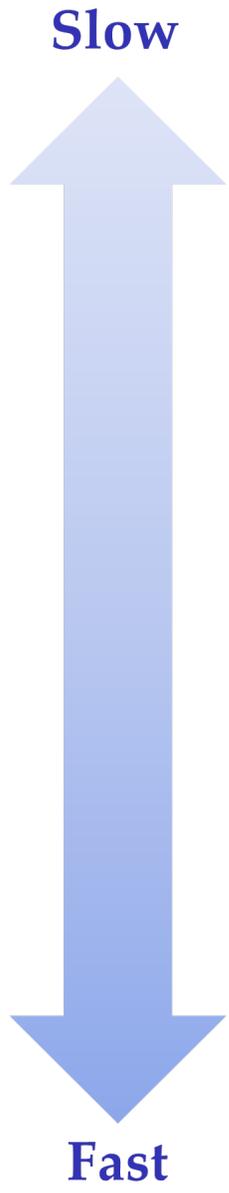
MPC constraint



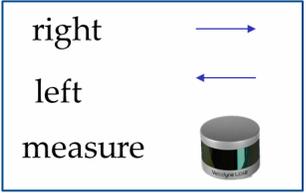
Nonlinear system

$$\dot{x} = f(x) + b(x)u$$

# Multi-Agent Autonomy



High Level: Decision Making



Frequency ~0.1Hz



Mid Level: Trajectory Planning



Frequency ~10Hz



Low Level: Control Actuators



Frequency ~1kHz

*POMDP planning*

*Model Predictive Control*

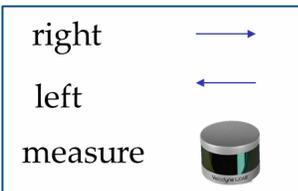
*Control Barrier Functions*



# Multi-Agent Autonomy

Slow

High Level: Decision Making



Frequency ~0.1Hz

Safe

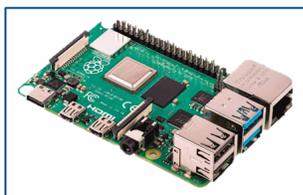
Mid Level: Trajectory Planning



Frequency ~10Hz

Safe

Low Level: Control Actuators



Frequency ~1kHz

POMDP planning

POMDP Planning

Minimize time to completion

$$\mu^s = \operatorname{argmin}_{\mu} \mathbb{E}^{\mu} \left[ \sum_{k=0}^N \mathbb{1}_{\mathcal{G}}(s_k^r) \right]$$

s.t.  $\mu \in \operatorname{argmax}_{\kappa} \mathbb{P}^{\kappa}[\omega^r \models \psi^r]$

Maximize probability of being safe

Robust MPC

$$\min_{u_0, \dots, u_{N-1}} \sum_{t=0}^N l(x_t, u_t) + Q(x_N)$$

s.t.  $x_{k+1} = A_k x_k + B_k u_k + w_k$   
 $x_k \in \mathcal{X}, u_k \in \mathcal{U}, \forall w_k \in \mathcal{W}$   
 $x_0 = x(t)$

Linearized model

Model errors

Model Predictive Control

CBF safe tracking

From MPC

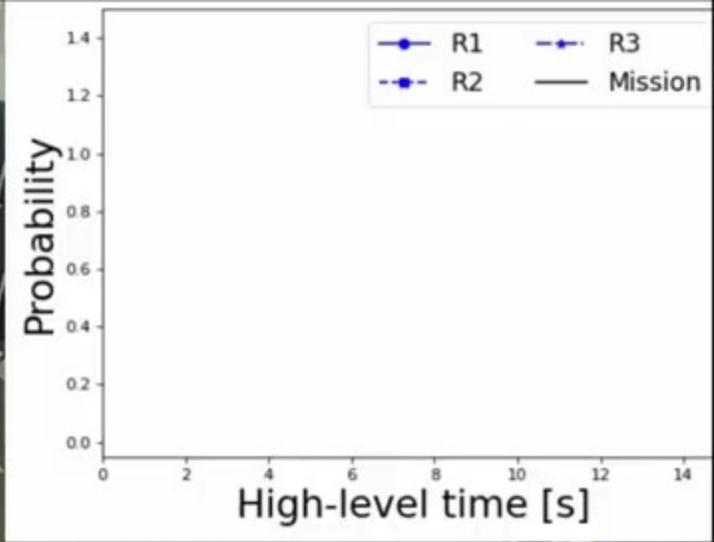
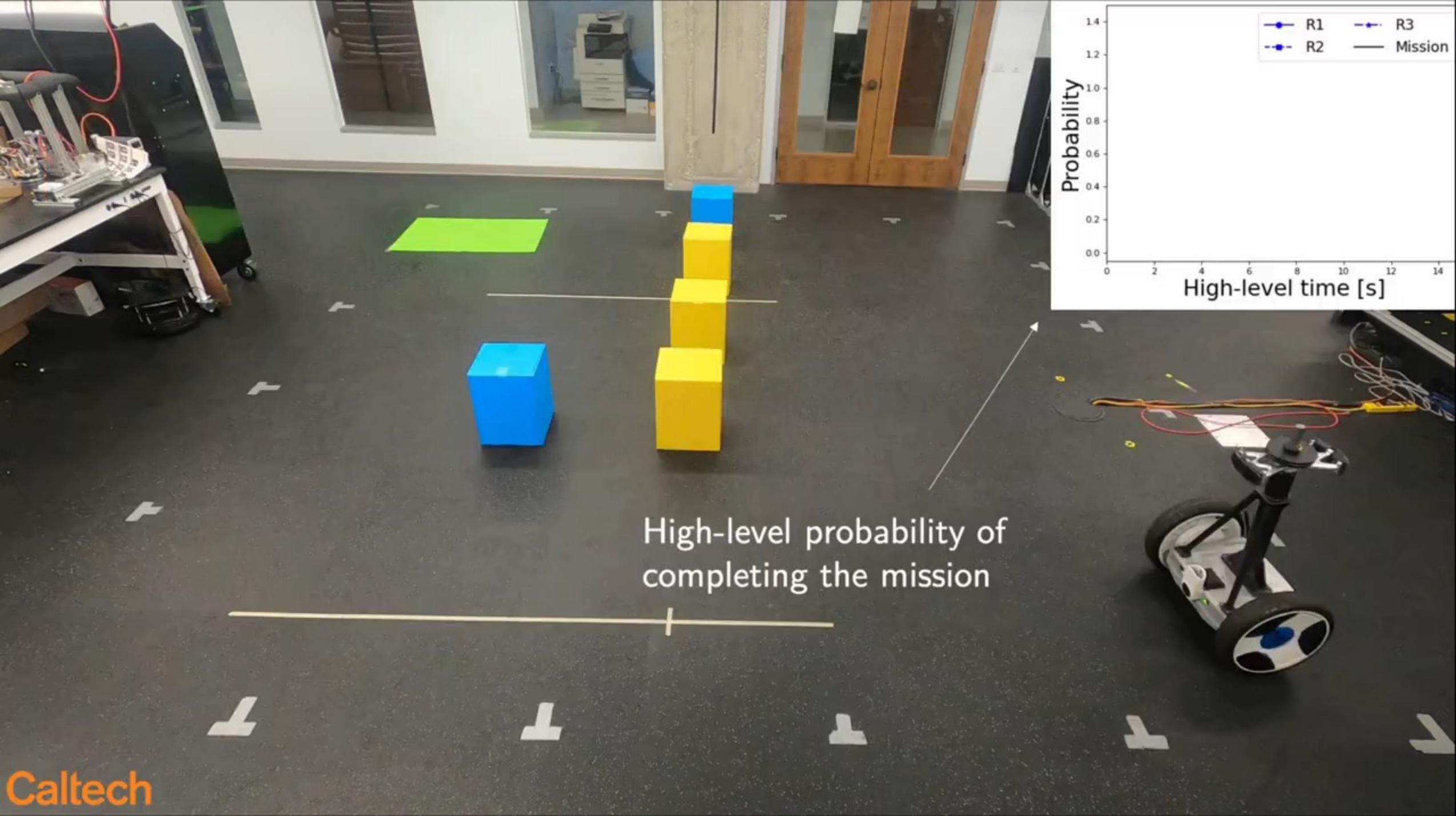
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s.t.  $\dot{h}(x, u) \geq -\alpha(h(x))$

Guarantees tracking error bounds

Control Barrier Functions

Fast

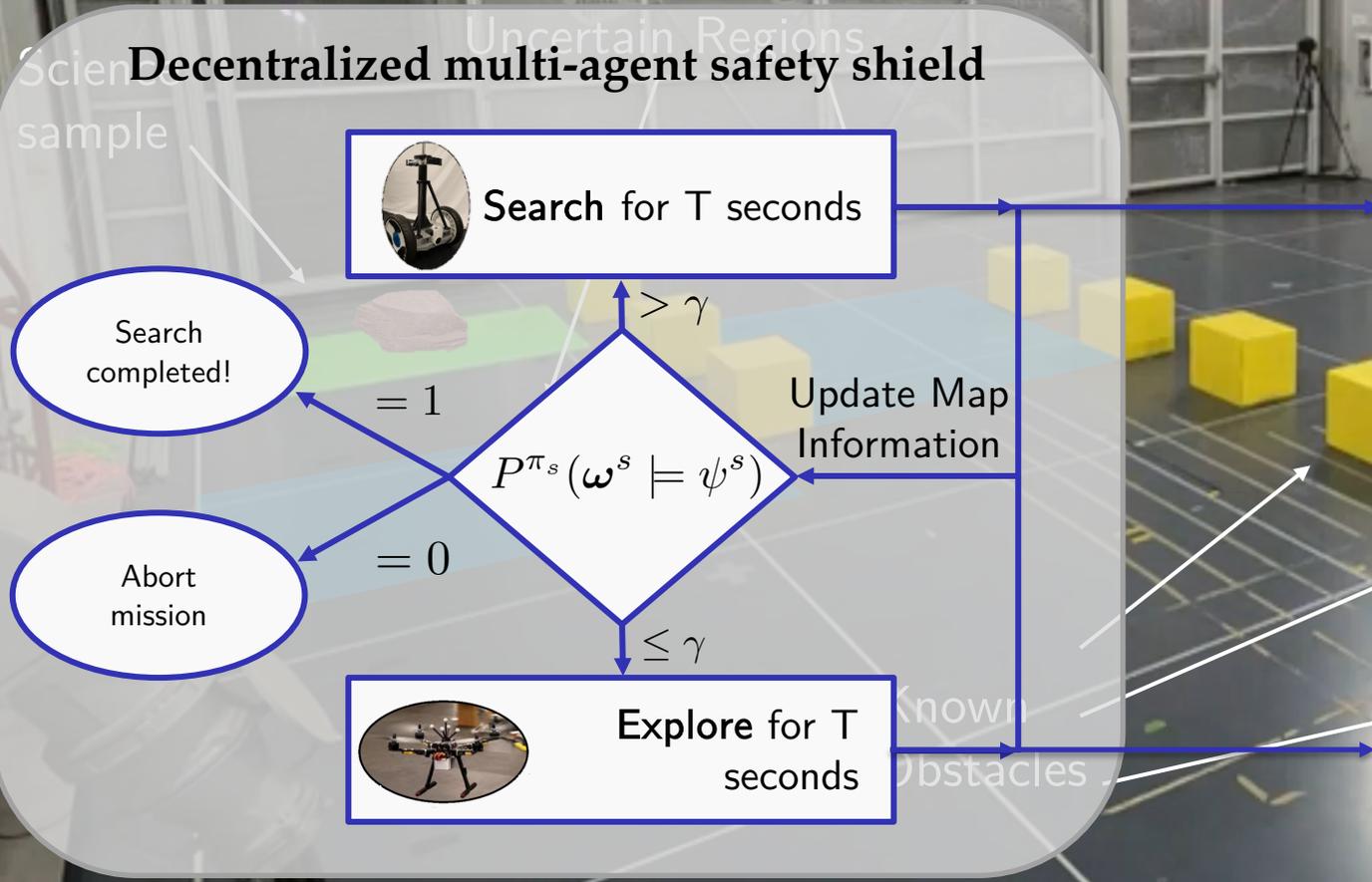


High-level probability of completing the mission

# Cooperative Task and Path Planning



Rover



### High-level Search Policy

Minimize time to completion

$$\mu^s = \operatorname{argmin}_{\mu} \mathbb{E}^{\mu} \left[ \sum_{k=0}^N \mathbb{1}_{\mathcal{G}}(s_k^r) \right]$$

s.t.  $\mu \in \operatorname{argmax}_{\kappa} \mathbb{P}^{\kappa}[\omega^r \models \psi^r]$

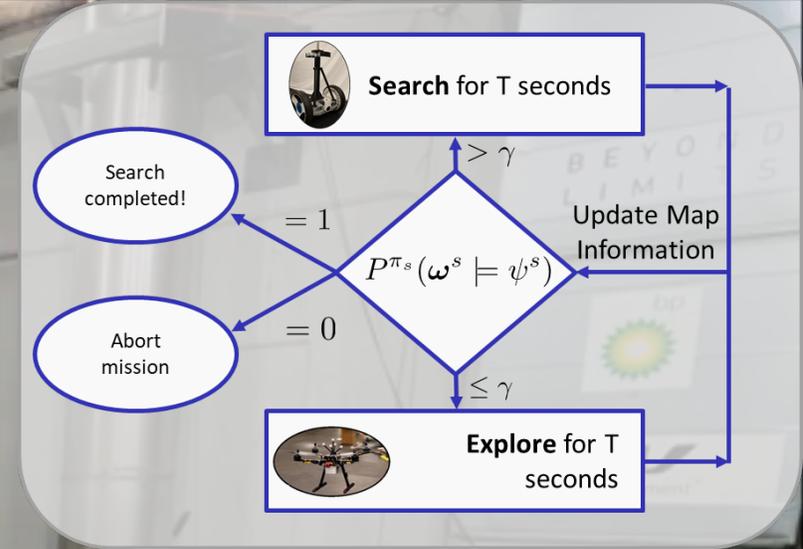
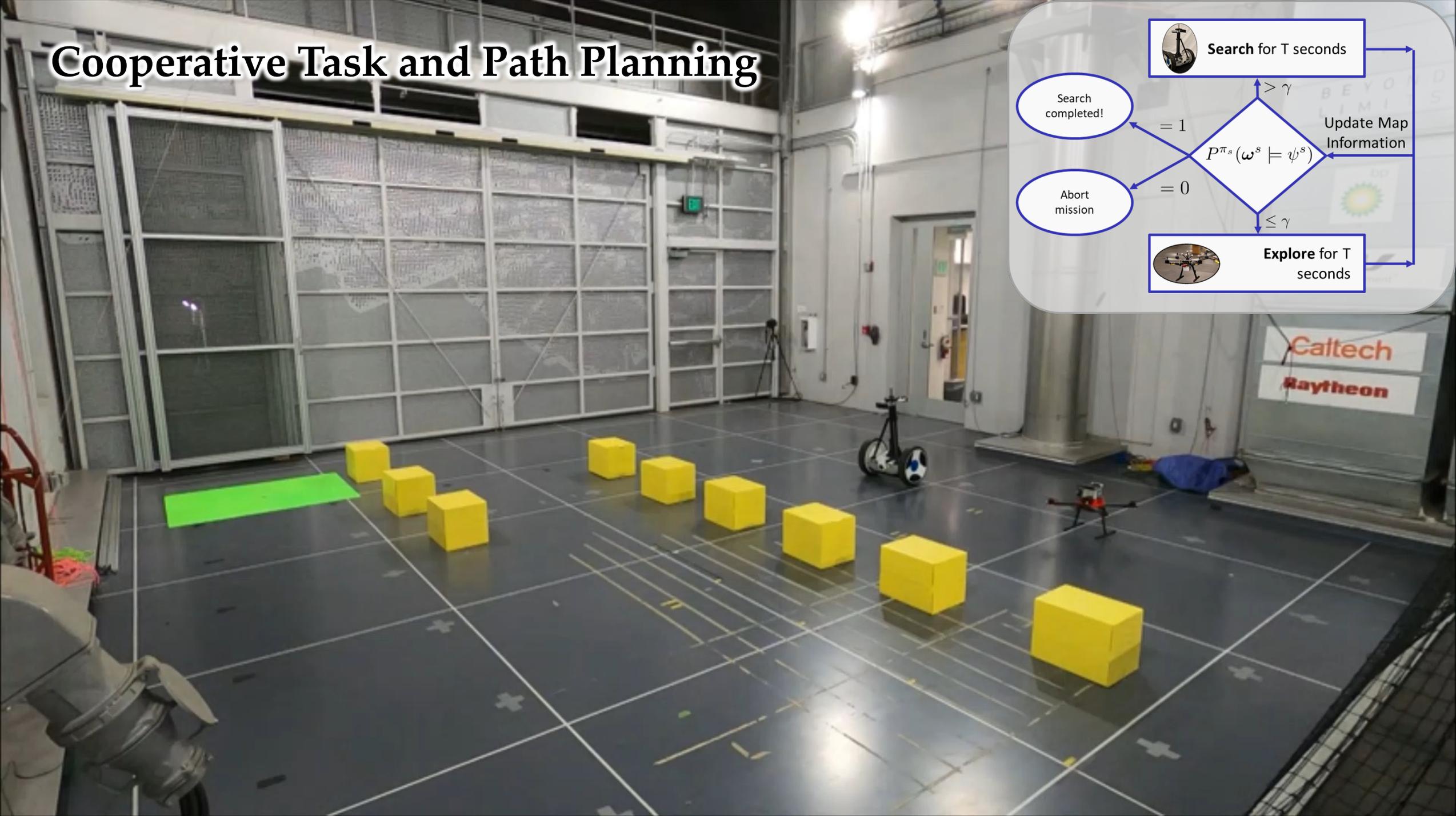
### High-level Explore Policy

Maximize probability of gathering useful measurements

$$\mu^e = \operatorname{argmax}_{\mu} \mathbb{E}^{\mu} \left[ \sum_{k=0}^N I(s_k^e) \right]$$

s.t.  $\mu \in \operatorname{argmax}_{\kappa} \mathbb{P}^{\kappa}[\omega^e \models \psi^e]$

# Cooperative Task and Path Planning



Caltech

# A Hierarchical Approach for Mission Planning in Partially Observable Environments

Ugo Rosolia, Andrew Singletary, Yuxiao Chen, Aaron D. Ames



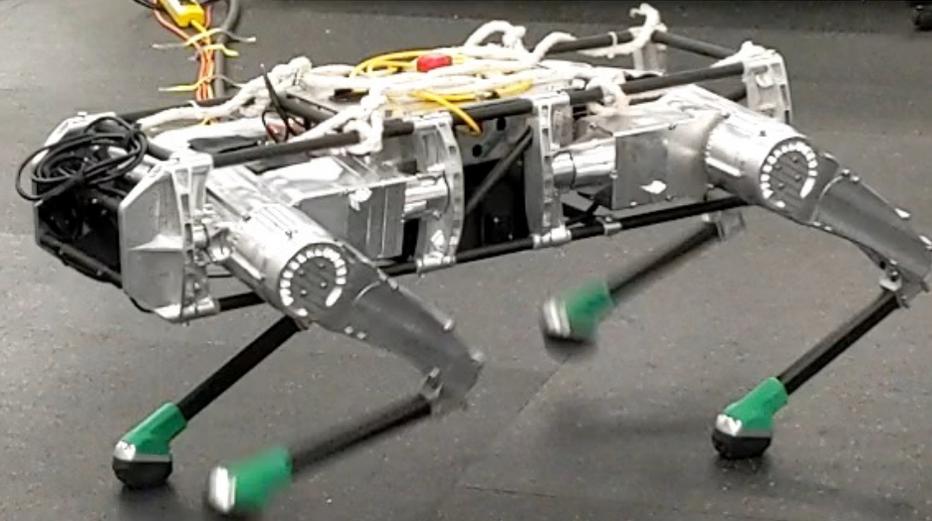
# Conclusion + Future Work

## Summary

- **Goal:** Safe Multi-Robot Systems
- Safety with Control Barrier Functions
- Safety at Discrete Planning level
- Towards the Unification Across Layers
- Experimental Realization

## Future Work

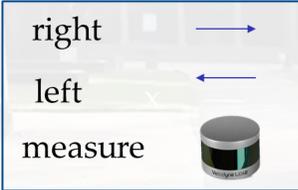
- **Goal:** Robust Real-World Autonomy
- Control Barrier Functions + Sensing
- Planning in Natural Environments
- Realization on Dynamic Robots
- [Applications to Space Exploration](#)
- [Applications to "Partners"](#)



# Next Steps: Real-World Autonomy

Slow

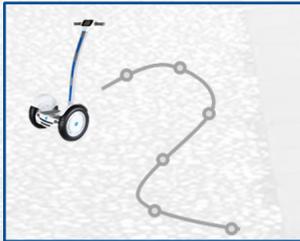
High Level: Decision Making



Frequency  $\sim 0.1\text{Hz}$



Mid Level: Trajectory Planning



Frequency  $\sim 10\text{Hz}$



Low Level: Control Actuators



Frequency  $\sim 1\text{kHz}$

Fast



## Thank You