



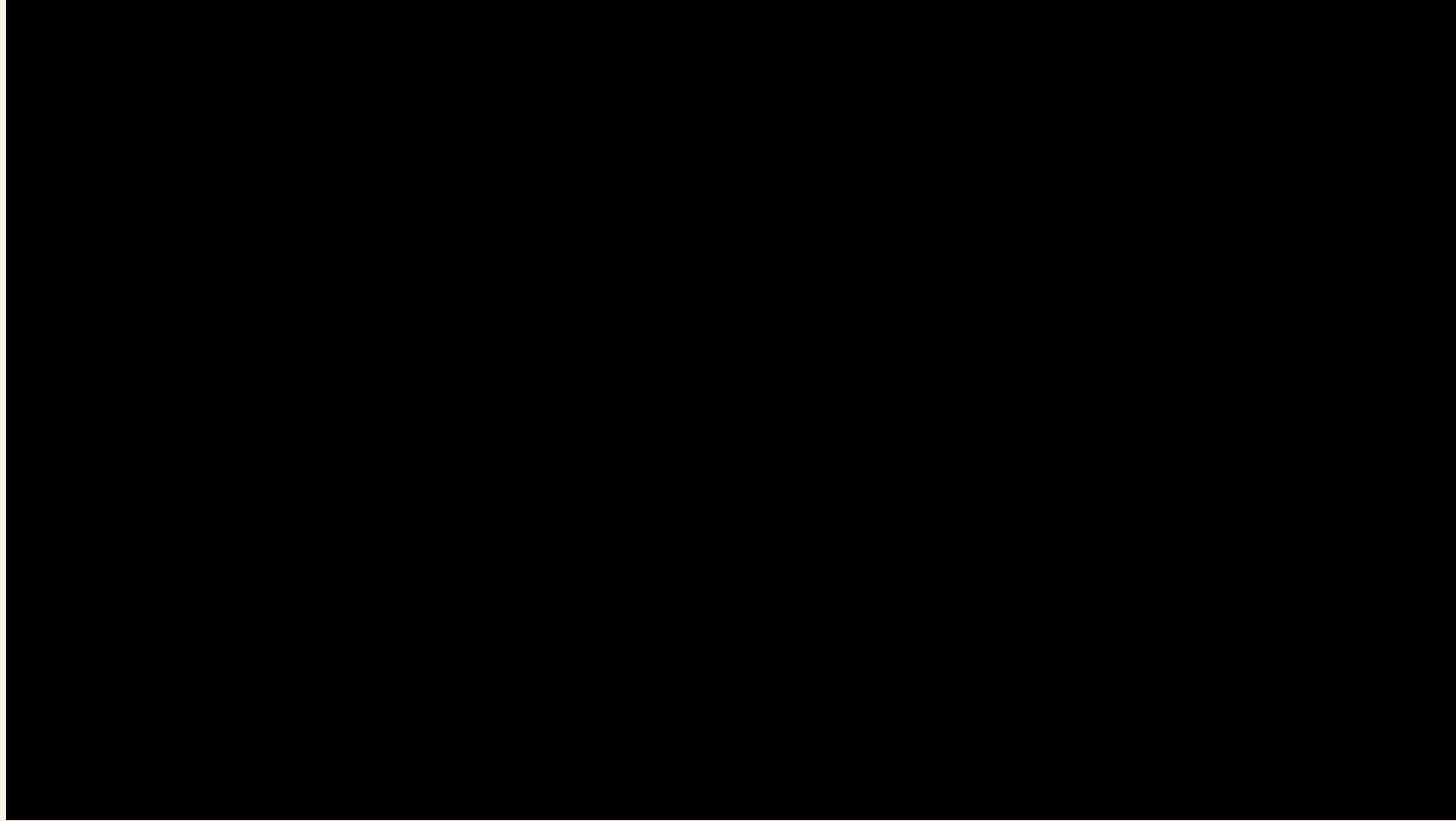
# Optimal Control of Differentially Flat Systems is Surprisingly Easy

**Logan E. Beaver, Ph.D.**

Assistant Professor of Autonomous Systems  
Department of Mechanical and Aerospace Engineering  
Old Dominion University

# Goal: Fast Motion Planning

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Parc du Haut-Fourneau U4 by TomFPV, Youtube

# OUTLINE

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01

Flatness + Optimal Control

02

The Problem with Constraints

03

Heuristic Algorithm

# Related Work

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## ◇ Method of Evolving Junctions

- Li, Chow, Egerstedt, Lu, and Zho, (2017); Zhai, Hou, Zhang, and Zhou, (2021)

## ◇ NOSNOC

- A.Nurkanović and M. Diehl (2022); A.Nurkanović et al., (2023)

## ◇ Collocation Methods

- Andersson, Gillis, Horn, Rawlings, and Diehl (2019), Ross (2012), Murray (2008), Wächter and Biegler (2006),

## ◇ Differential Flatness

- Fleiss et al., (1995); Petit, Milam, and Murray, (2001); Sira-Ramirez and Agrawal, (2004); Chaplais and Petit, (2007, 2008); Levine, (2011)

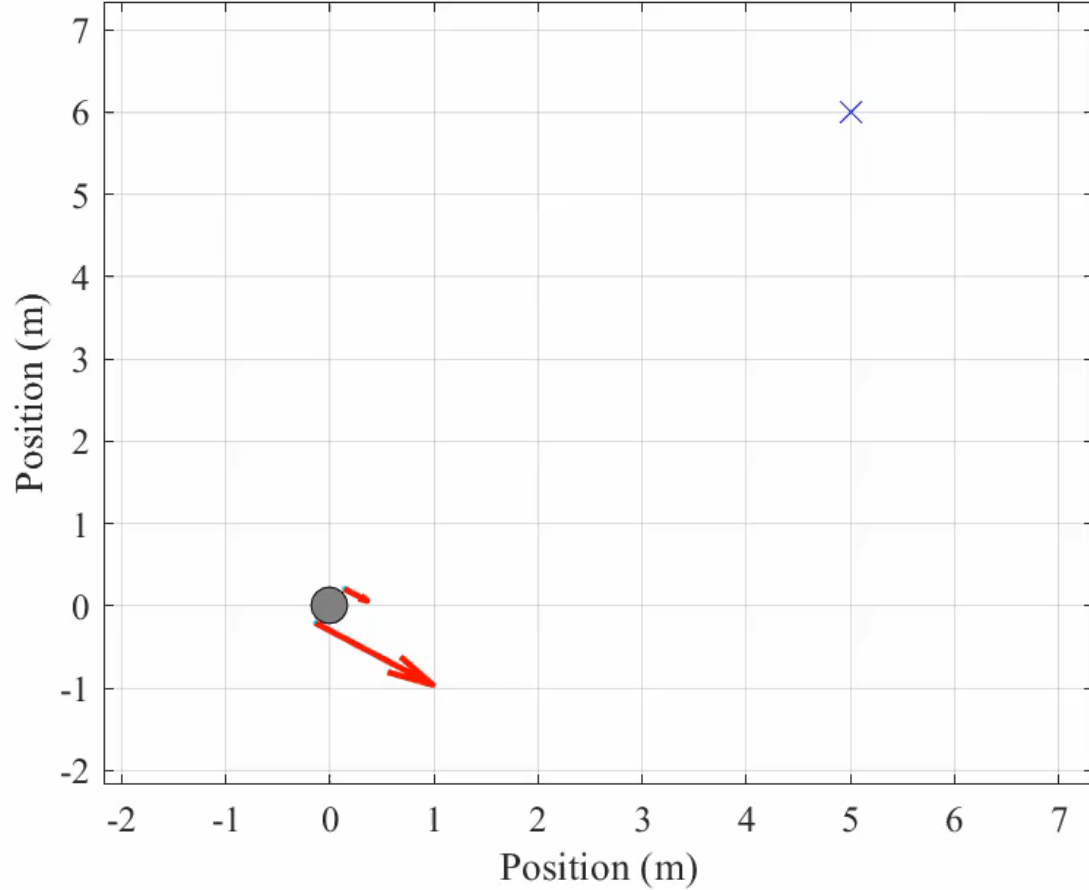
# Flatness + Optimal Control

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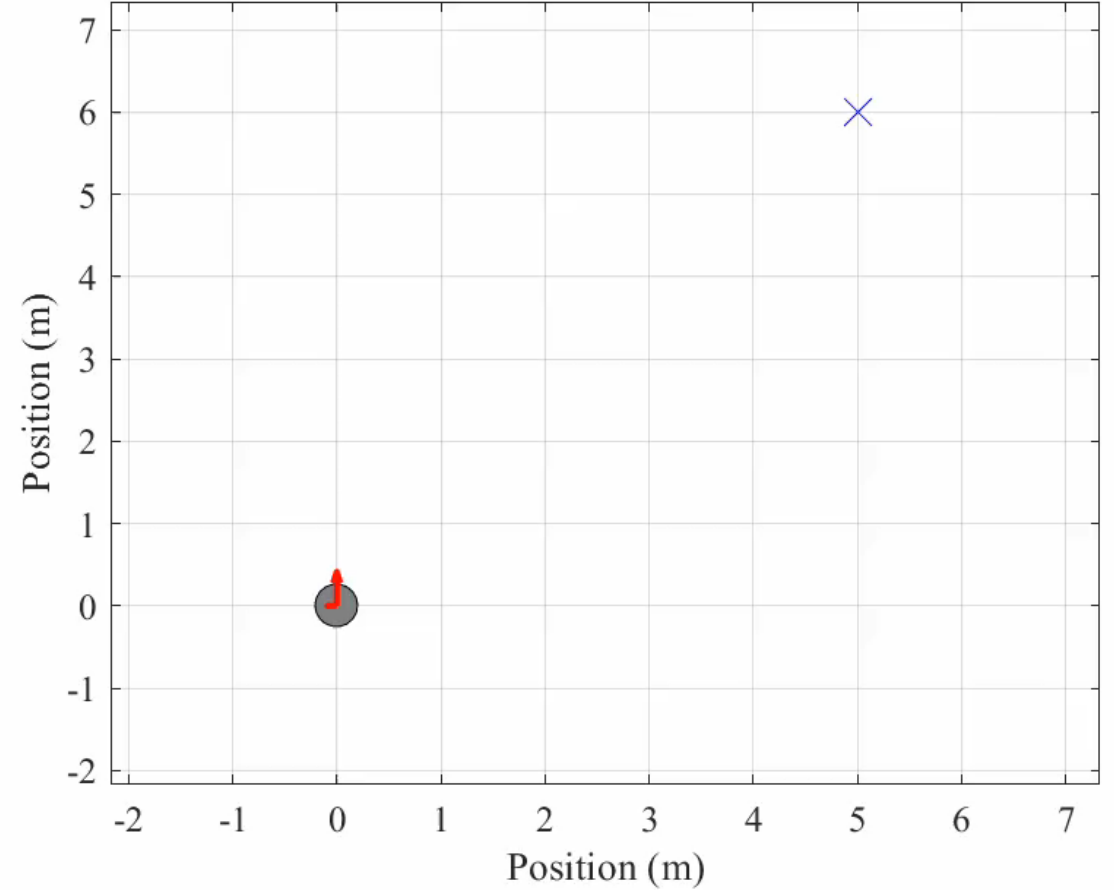
1. **Beaver, L. E.**, & Malikopoulos, A. A. (2024). Optimal control of differentially flat systems is surprisingly easy. *Automatica*, 159, 111404.
2. **Beaver, L. E.** (2023). LQ-OCP: Energy-optimal control for lq problems. *2024 American Control Conference (to appear)*
3. Chalaki, B., **Beaver, L. E.**, & Malikopoulos, A. A. (2020). Experimental validation of a real-time optimal controller for coordination of cavs in a multi-lane roundabout. In *2020 IEEE Intelligent Vehicles Symposium (IV)* (pp. 775-780). IEEE.
4. **Beaver, L. E.**, & Malikopoulos, A. A. (2019). A decentralized control framework for energy-optimal goal assignment and trajectory generation. In *2019 IEEE 58th Conference on Decision and Control (CDC)* (pp. 879-884). IEEE.
5. **Beaver, L. E.**, & Malikopoulos, A. A. (2019). A decentralized control framework for energy-optimal goal assignment and trajectory generation. In *2019 IEEE 58th Conference on Decision and Control (CDC)* (pp. 879-884). IEEE.

# Differential Flatness

Original Coordinates

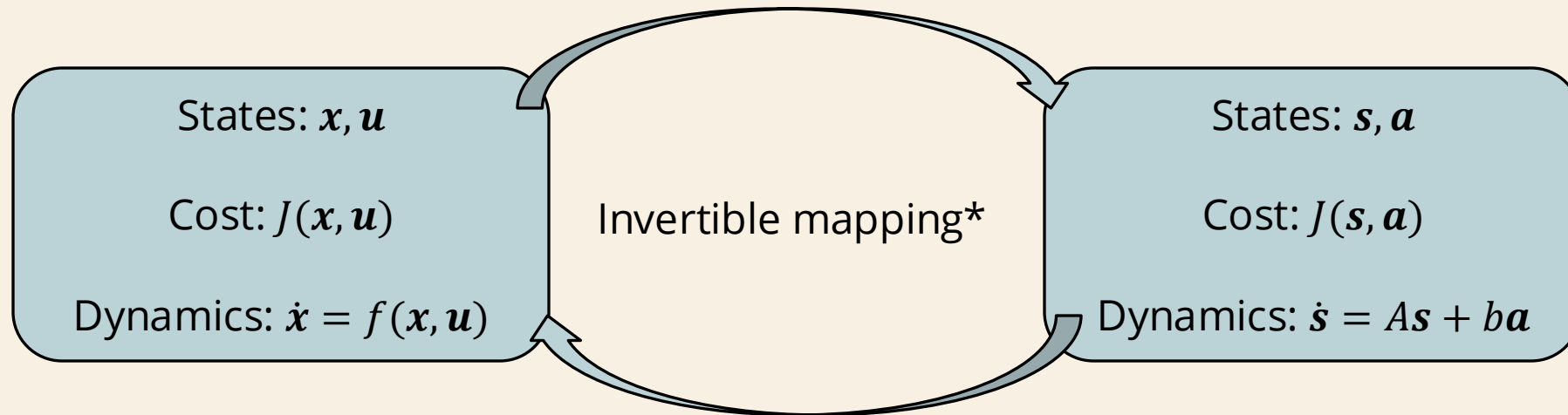


Flat Coordinates



# Differential Flatness

- ◇ Property of nonlinear systems
- ◇ Mapping between coordinates\*
- ◇ New system has linear dynamics



\*no exogenous coordinates, differentially independent

# Differential Drive Robot

- ◇ Original Coordinates

$\mathbf{p}, \theta, v_L, v_R$



$$\omega = \frac{v_R - v_L}{L}$$
$$v = \frac{v_R + v_L}{2}$$

- ◇ Polar Coordinates

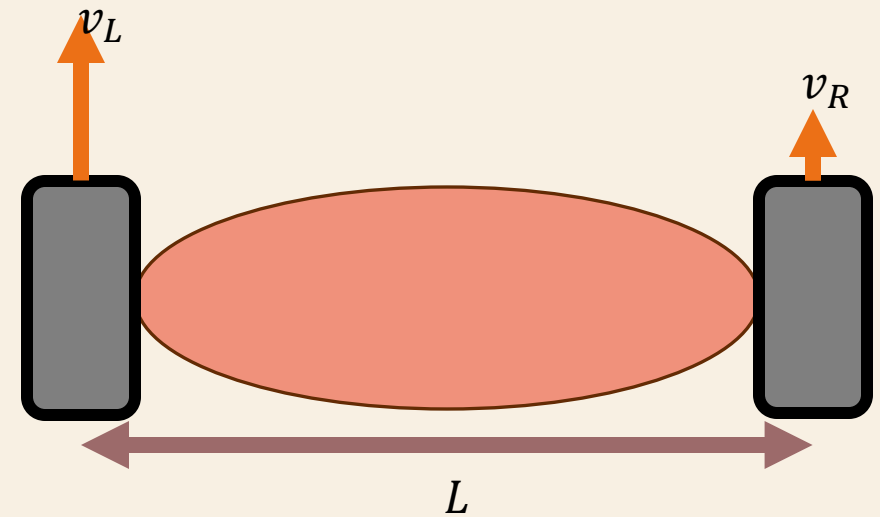
$\mathbf{p}, v, \theta, \omega$



$$\frac{v_y}{v_x} = \tan(\theta)$$
$$\|\mathbf{v}\| = v$$

- ◇ Flat Coordinates

$\mathbf{p}, v$





# PMP for Linear Systems

- ◇ Follow the *standard approach* of Bryson and Ho

$$H(\mathbf{s}, \mathbf{a}, \lambda) = J(\mathbf{s}, \mathbf{a}) + \lambda \cdot \mathbf{f}(\mathbf{s}, \mathbf{a}) + \mu \cdot \mathbf{g}(\mathbf{s}, \mathbf{a})$$

- ◇ Minimize the Hamiltonian

$$\frac{\partial H}{\partial \mathbf{a}} = 0$$

$$\dot{\lambda} = \frac{\partial H}{\partial \mathbf{s}}$$

- ◇ Numerically unstable ODE in general

# Linear Systems Trick

$$H(\mathbf{s}, \mathbf{a}, \boldsymbol{\lambda}) = J(\mathbf{s}, \mathbf{a}) + \boldsymbol{\lambda} \cdot \mathbf{f}(\mathbf{s}, \mathbf{a}) + \boldsymbol{\mu} \cdot \mathbf{g}(\mathbf{s}, \mathbf{a})$$

- ◇ Partial derivatives simplify!

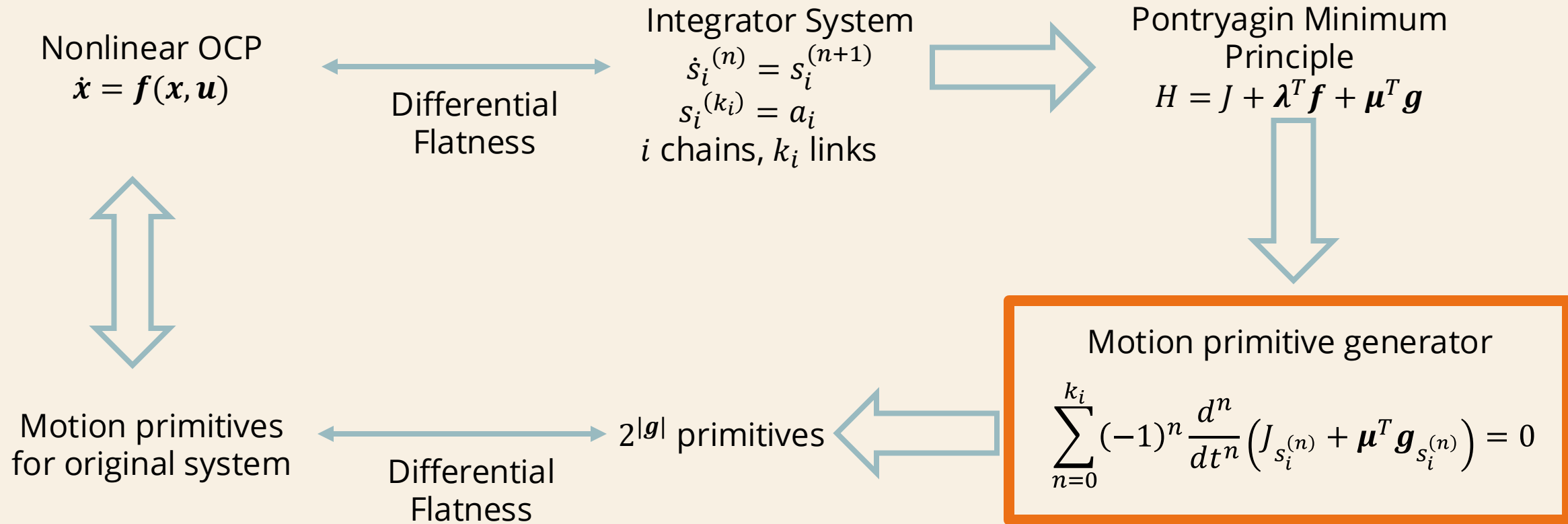
$$\frac{\partial \mathbf{f}}{\partial \mathbf{s}} = \frac{\partial}{\partial \mathbf{s}} A\mathbf{s} + b\mathbf{a} = A$$

$$\frac{\partial \mathbf{f}}{\partial \mathbf{a}} = \frac{\partial}{\partial \mathbf{a}} A\mathbf{s} + b\mathbf{a} = b$$

- ◇ Resulting ODEs,

$$J_{\mathbf{a}} + \boldsymbol{\lambda}^T b + \boldsymbol{\mu}^T \mathbf{g}_{\mathbf{a}} = 0$$
$$\dot{\boldsymbol{\lambda}}_x = -J_{\mathbf{s}} - \boldsymbol{\lambda}^T A + \boldsymbol{\mu}^T \mathbf{g}_{\mathbf{s}}$$

# Solution Overview



# Dynamic Motion Primitives

$$\sum_{n=0}^{k_i} (-1)^n \frac{d^n}{dt^n} \left( J_{s_i}^{(n)} + \boldsymbol{\mu}^T \mathbf{g}_{s_i}^{(n)} \right) = 0$$

- ◇ Toggle elements of  $\boldsymbol{\mu}$  “on” and “off”
- ◇ Solve ODE + algebraic equations to generate motion primitives
- ◇ At most  $2^{|g|}$  cases

# The Problem with Constraints

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1. **Beaver, L. E.**, Tron, R., & Cassandras, C. G. (2023). A graph-based approach to generate energy-optimal robot trajectories in polygonal environments. *IFAC-PapersOnLine*, 56(2).
2. Malikopoulos, A. A., **Beaver, L.**, & Chremos, I. V. (2021). Optimal time trajectory and coordination for connected and automated vehicles. *Automatica*, 125, 109469.

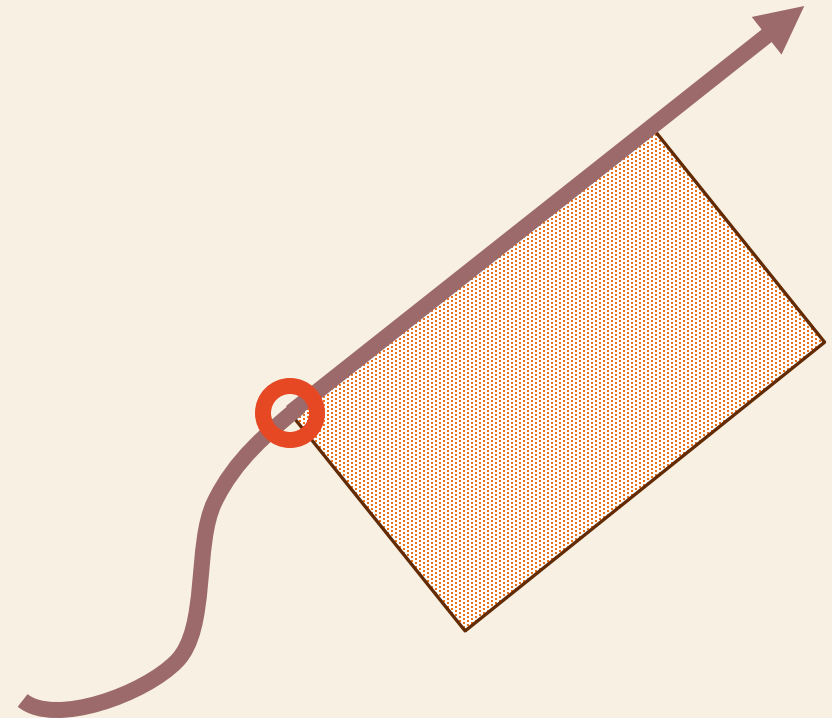
# Constraint Junctions

- ◇ Known “standard” form at time  $t_1$

$$H(t_1^-) = H(t_1^+) + \pi \frac{\partial N}{\partial t}$$

$$\lambda^T(t_1^-) = \lambda^T(t_1^+) + \pi \frac{\partial N}{\partial x}$$

- ◇ Easily converts to state conditions



# Shooting Method

- ◇ Given a constraint sequence,
  - ◇ Apply jump conditions for  $\lambda, H$
  - ◇ For example,  $\|a\|^2$  in cost  $\rightarrow$  continuity in  $a$

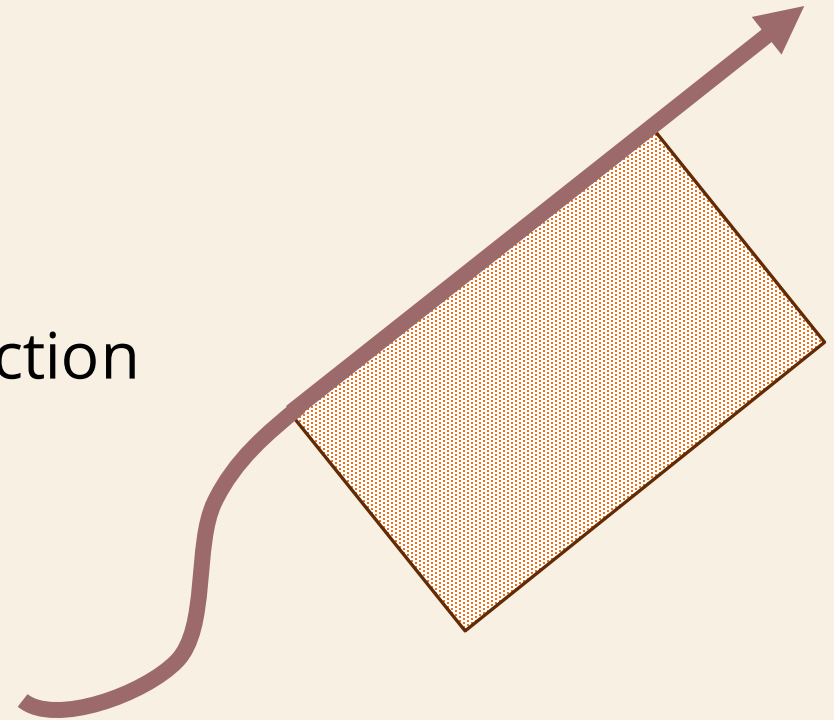
$$a(t_1^-) = a(t_1^+)$$

- ◇ System of algebraic equations at the junction

$$x(t_1^-) = x(t_1^+)$$

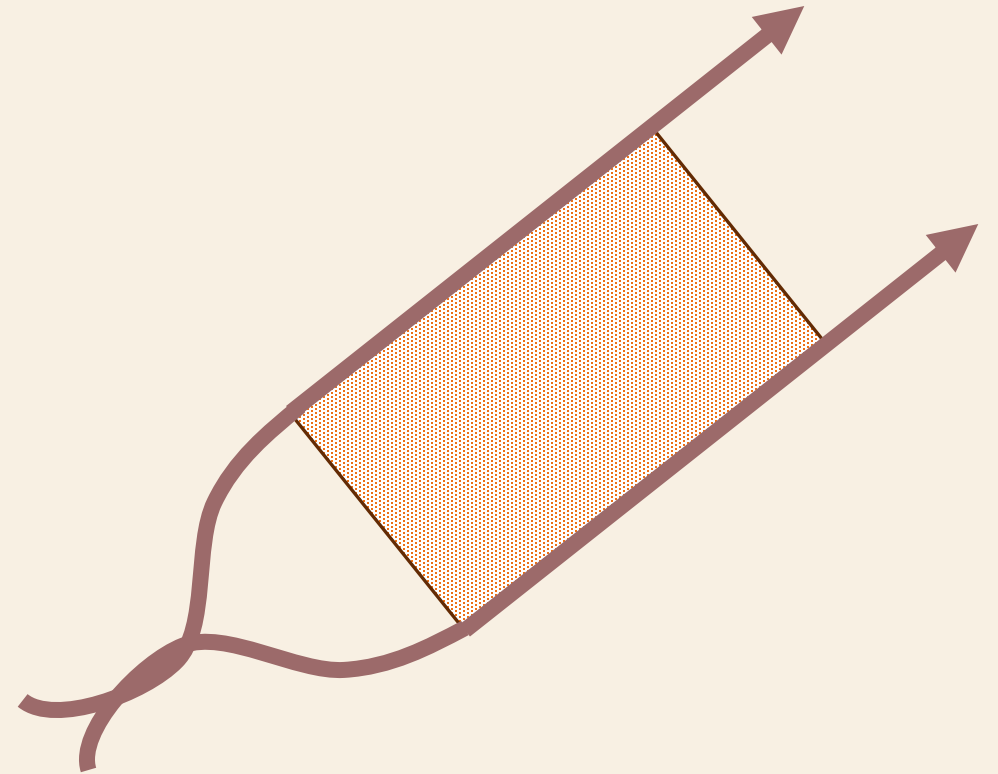
$$u(t_1^-) = u(t_1^+)$$

- ◇ Linear for a “guess” of  $t_1$ 
  - ◇ 1 Equation + 1 unknown



# Optimal Trajectories

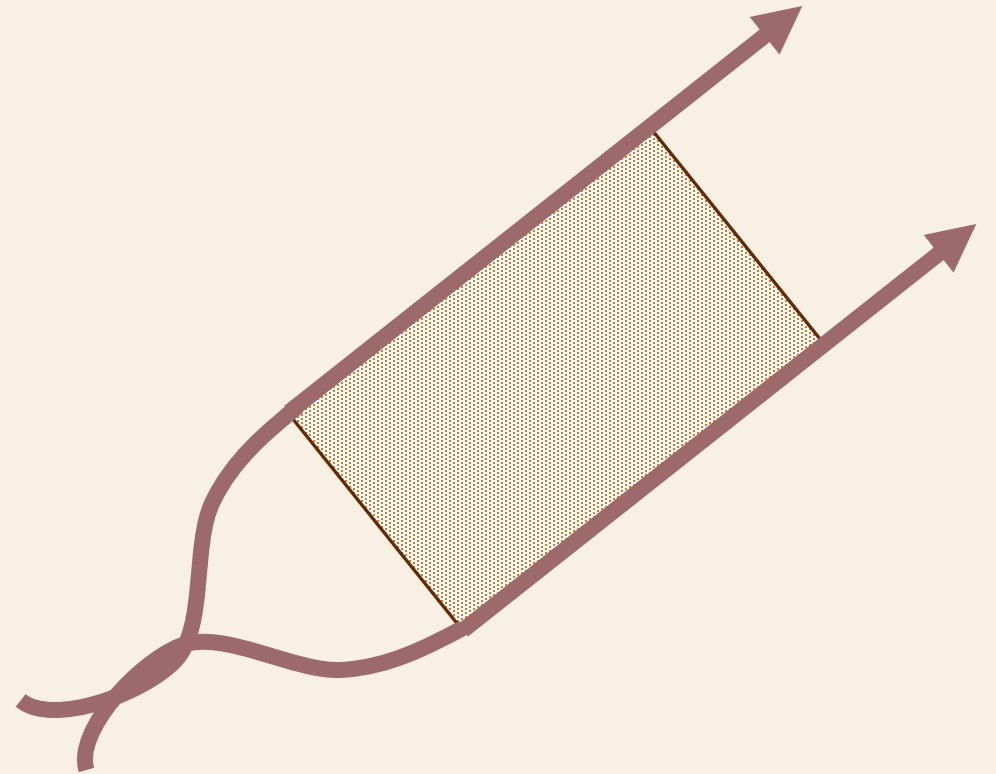
- ◇ Given a constraint, easy to solve
- ◇ **What is the optimal sequence?**



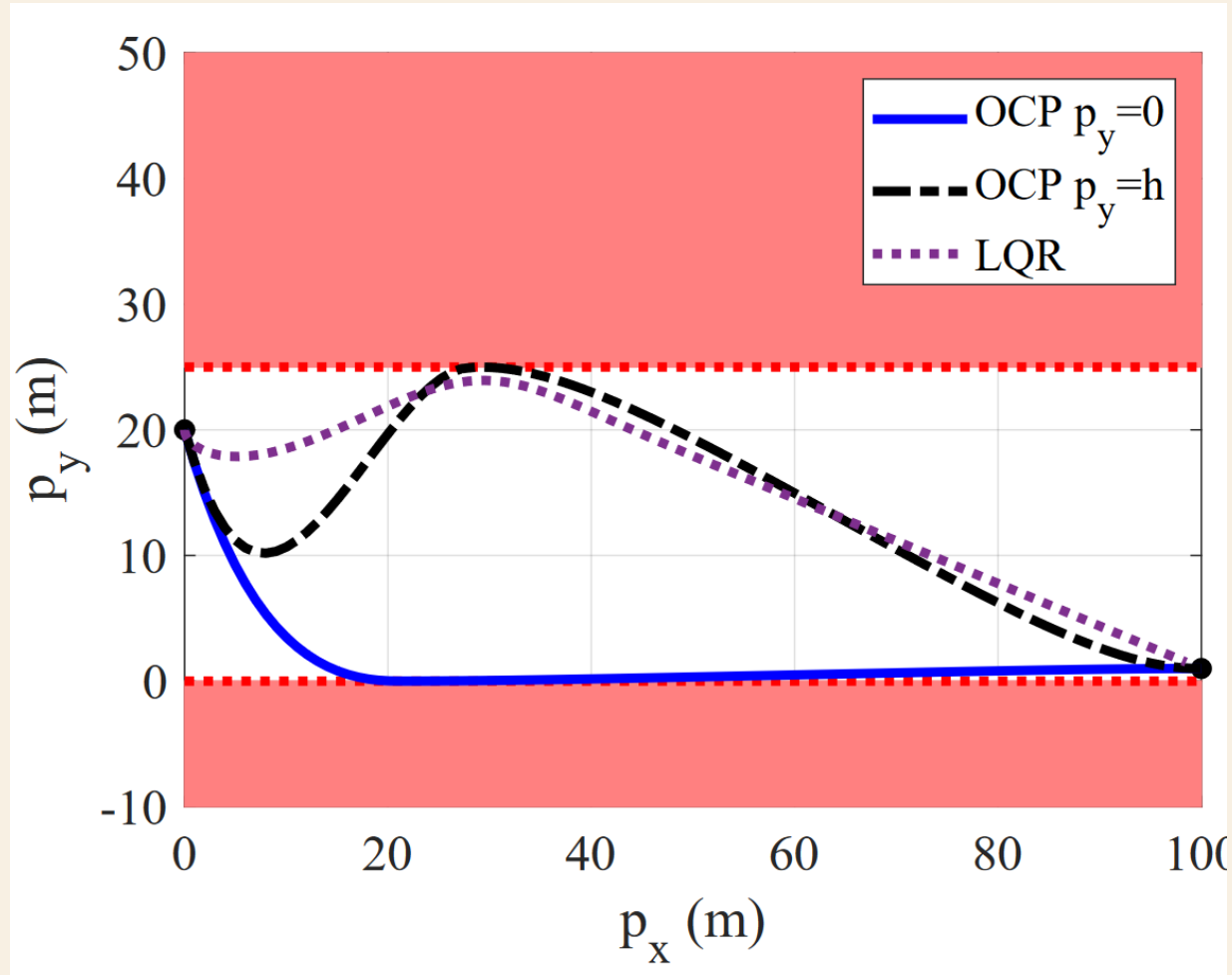


# Implications

- ◇ Both solutions satisfy PMP
- ◇ Both solutions are **convex**
- ◇ **Any** constraint breaks convexity!
- ◇ NP-Hard integer program?



# ACC Example



	Energy Cost	Optimality Gap
OCP with $v_y(t_1) = 0$	8,458 units	0%
OCP with $v_y(t_1) = h$	8,561 units	1.2%

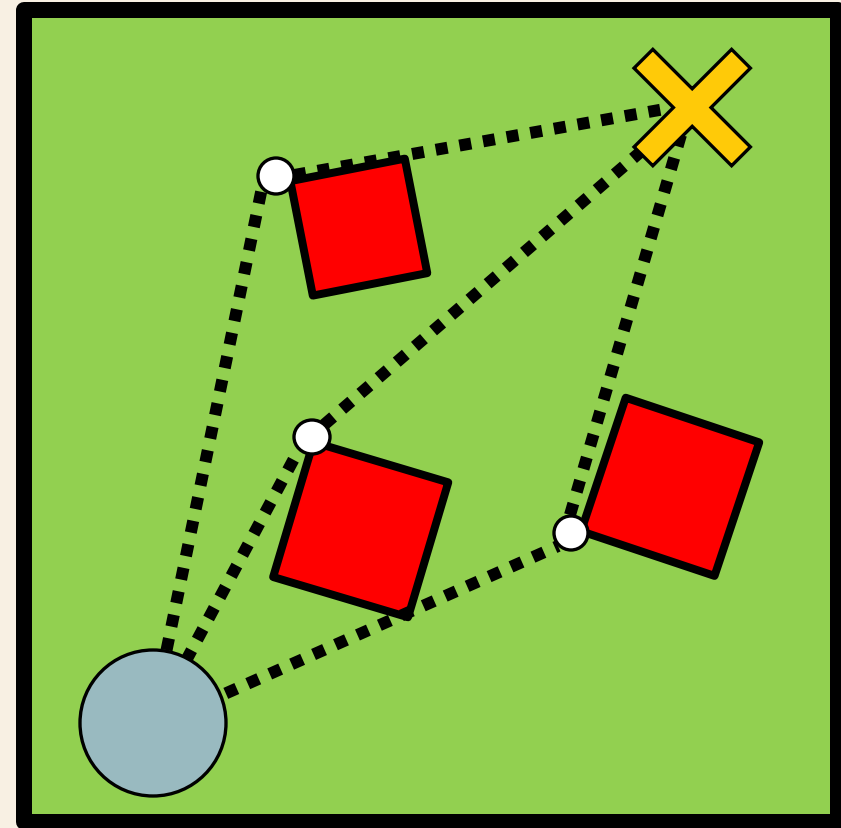
# Heuristic Algorithm

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1. **Beaver, L. E.**, Tron, R., & Cassandras, C. G. (2023). A graph-based approach to generate energy-optimal robot trajectories in polygonal environments. *IFAC-PapersOnLine*, 56(2).
2. Malikopoulos, A. A., **Beaver, L.**, & Chremos, I. V. (2021). Optimal time trajectory and coordination for connected and automated vehicles. *Automatica*, 125, 109469.

# Shooting Method Decomposition

- ◇ Motion primitives connected with junctions
- ◇ Solve optimal trajectory given the active constraints
- ◇ Which constraints to consider?



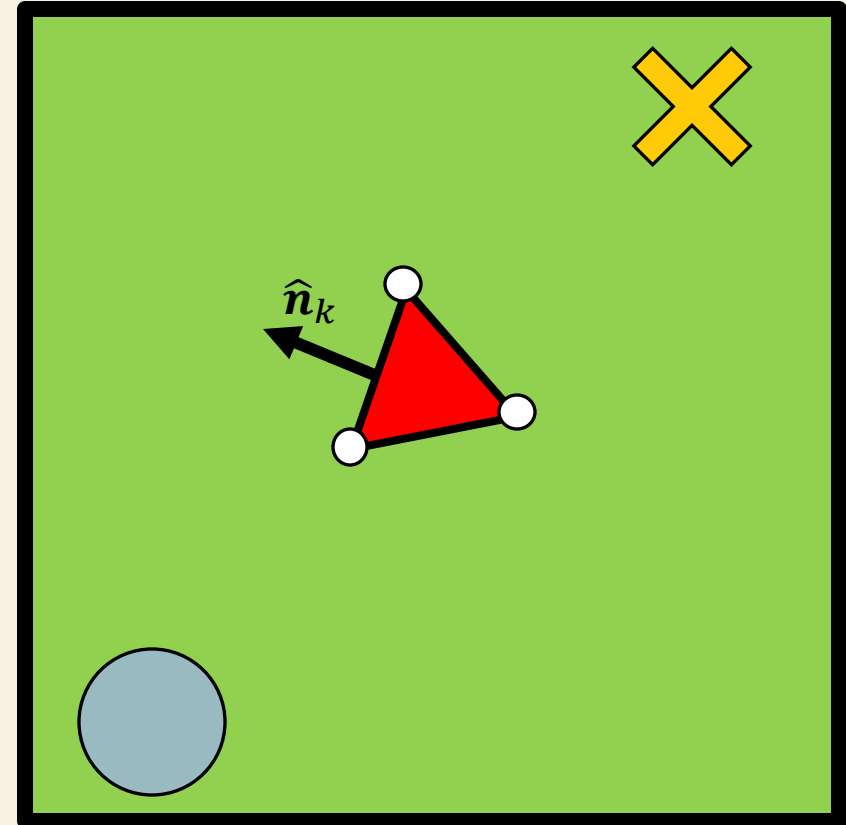
# Resulting Splines + Optimality

$$\sum_{n=0}^{k_i} (-1)^n \frac{d^n}{dt^n} \left( J_{s_i^{(n)}} + \boldsymbol{\mu}^T \mathbf{g}_{s_i^{(n)}} \right) = 0$$

- ◇ Unconstrained:  $\ddot{\mathbf{u}}^* = \mathbf{0}$
- ◇ Constrained:  $\mathbf{u}^* \cdot \hat{\mathbf{n}}_k = 0$

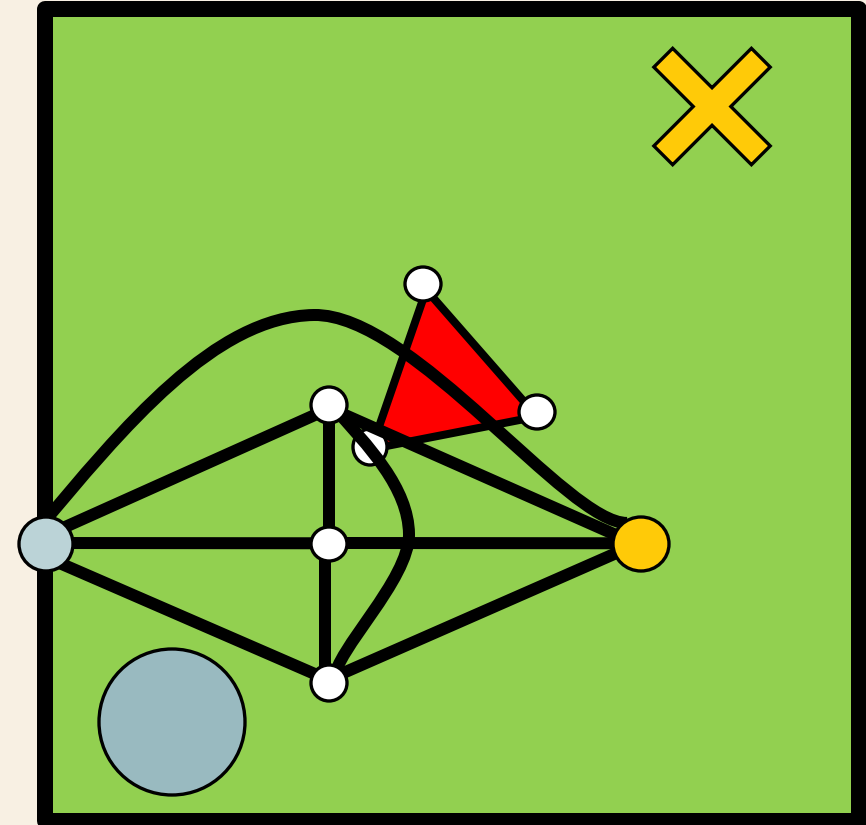
At junctions:

- ◇ Continuity in  $\mathbf{x}^*, \mathbf{u}^*, \mathbf{v}^{*T} \dot{\mathbf{u}}^*$
- ◇ Unknown  $\mathbf{x}^*, \mathbf{t}^*$  at junction

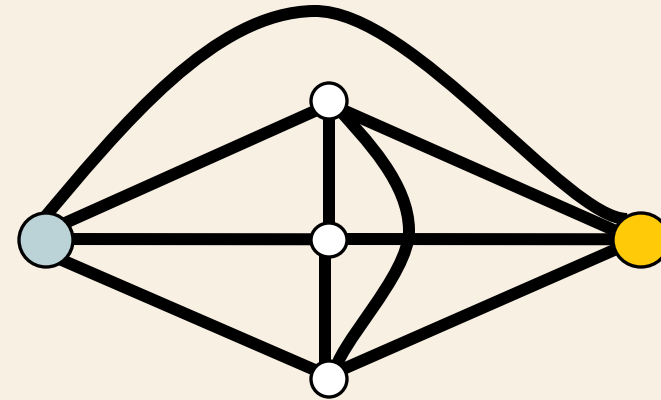
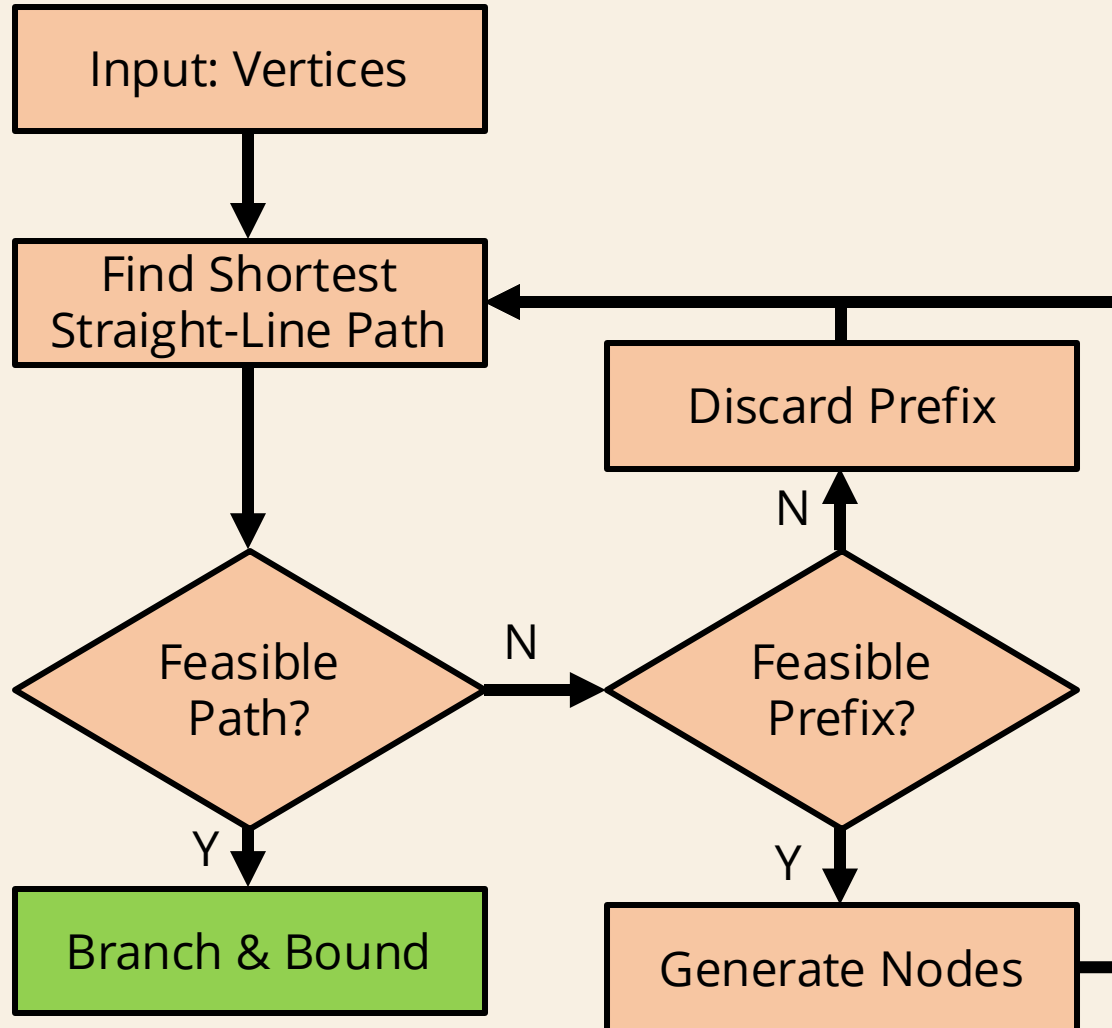


# The Integer Problem

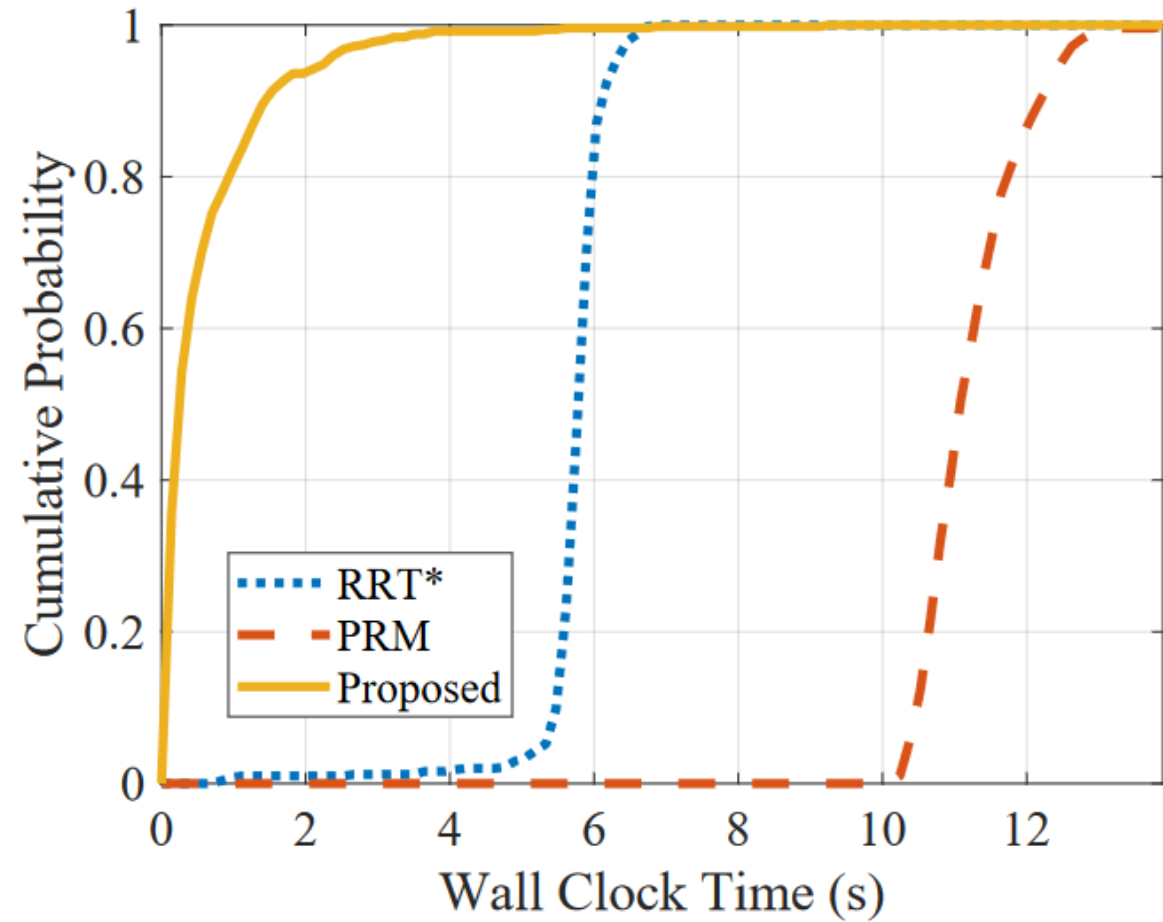
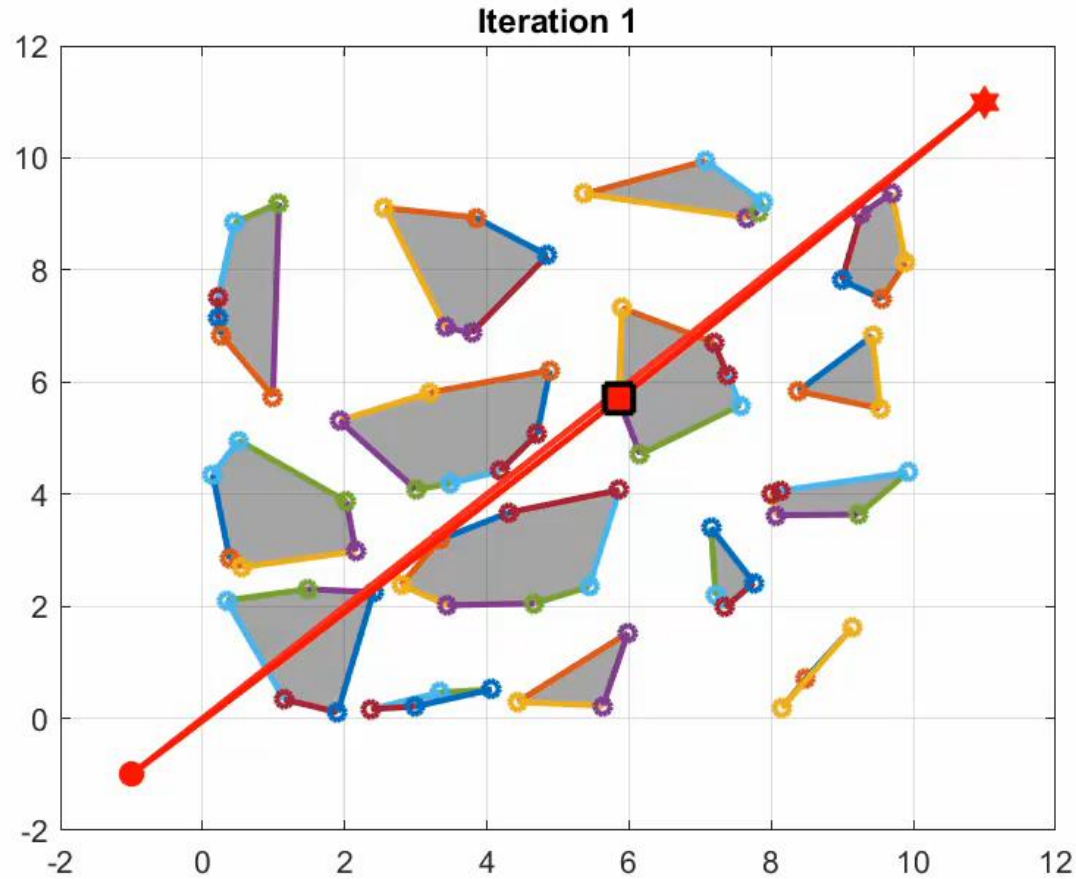
- ◇ OCP is easy, given constraints
- ◇ Which constraints to select?
  - ◇ Fully-connected graph, unknown cost
  - ◇ No admissible heuristic



# Search-Based Solution



# Constrained Motion Planning



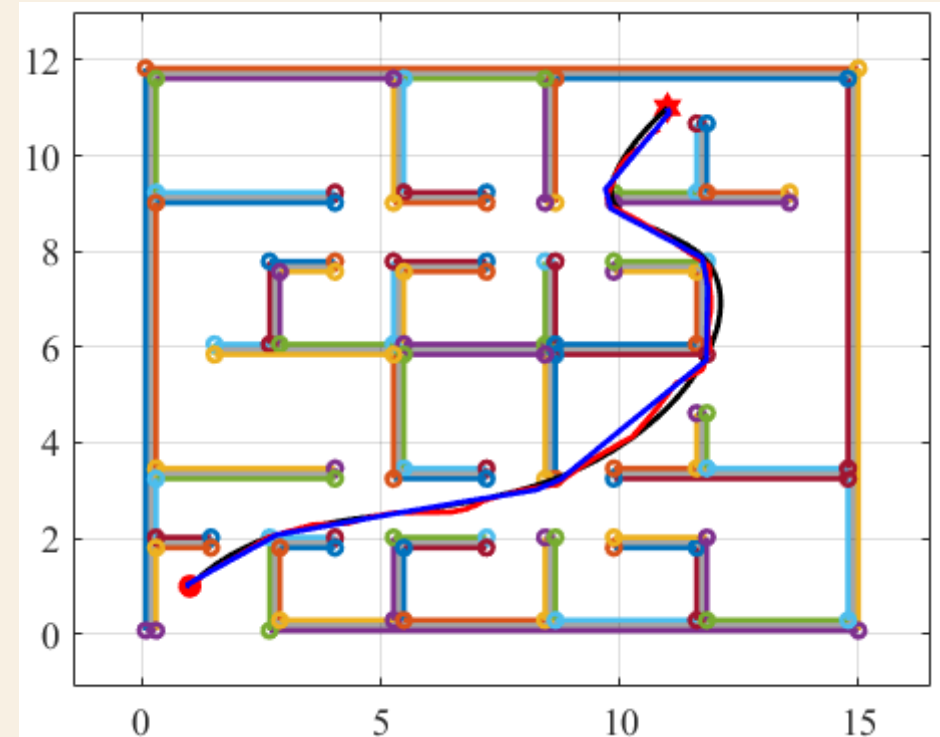
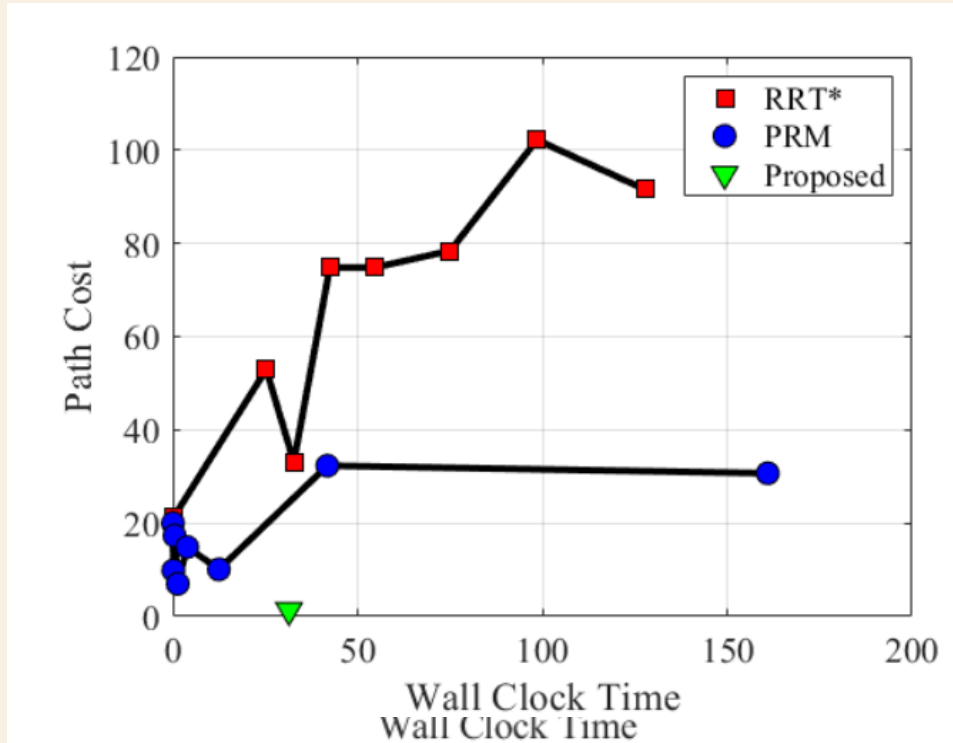
72 constraints (5184 combinations)

1. **Beaver**, Tron, and Cassandras, *A Graph-Based Approach to Generate Energy-Optimal Robot Trajectories in Polygonal Environments*, **2023 IFAC World Congress (to appear)**, 2023



# Maze Solving

- ◇ Proposed vs RRT and PRM



# High Degree of Freedom Systems

- ◇ Scales with number of vertices
- ◇ “Independent” of dimension
- ◇ Environmental preprocessing?



Image: Wikimedia commons

# Main Takeaways

- ◇ Flatness makes optimal control “easy”
- ◇ Out-performs state-of-the-art planning
- ◇ Constraints (even linear) cause problems
- ◇ Hybrid optimal + sampling techniques?

