

# *On the Convergence of Sequential Convex Programming for Non-Linear Optimal Control*

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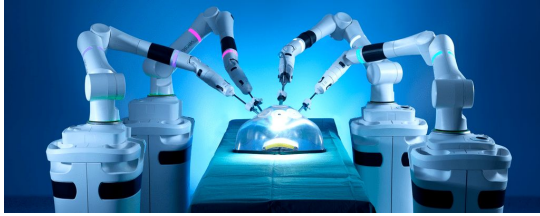


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# Complex autonomous systems are everywhere

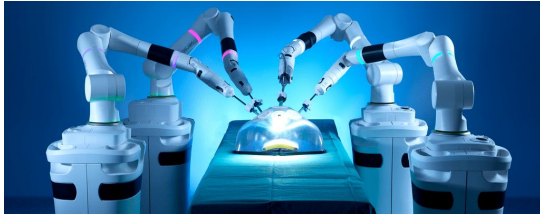


**Goal**

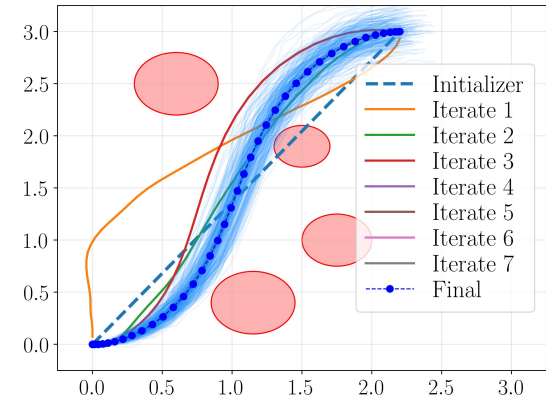
**Select the best  
available strategy and  
make robust decisions  
under uncertainty**



# Complex autonomous systems are everywhere



**Goal**  
Select the best available strategy and make robust decisions under uncertainty



# Optimal control of finite-dimensional dynamical systems

$$\min_{u \in \mathcal{U}} \int_0^{t_f} f^0(s, u(s), x(s)) \, ds$$

← Cost

$$dx(s) = f(s, u(s), x(s)) \, ds$$

← Dynamics

$$x(0) = x^0, \quad g(x(t_f)) = 0$$

← Initial / Final Conditions

$$h(x(s)) \leq 0, \quad s \in [0, t_f]$$

← State Constraints



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$$\min_{u \in \mathcal{U}} \mathbb{E} \left[ \int_0^{t_f} f^0(s, u(s), x(s)) ds \right]$$

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$$dx(s) = f(s, u(s), x(s)) ds + \sigma(s, x(s)) dB_s$$

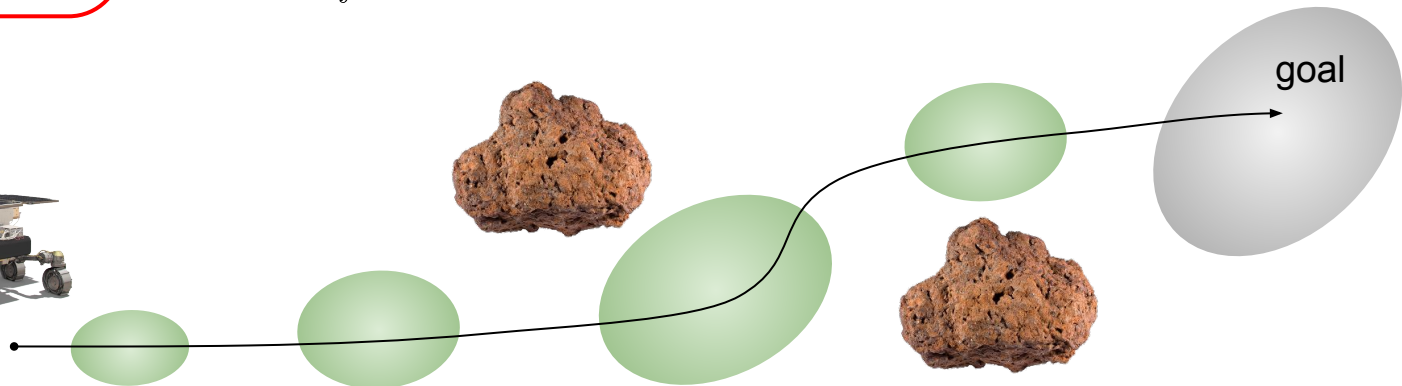
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# Several approaches have already been proposed

## Linear systems:

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- **J.M. Bismut, *Linear quadratic optimal stochastic control with random coefficients*, SIAM J. Control, 14(3): 419-444, 1976.**
- S. Chen, X. Li, and X. Zhou, *Stochastic linear quadratic regulators with indefinite control weight costs*, SIAM J. Control, 36(5): 1685-1702, 1998.
- T.E. Duncan, B. Pasik-Duncan, *Stochastic linear-quadratic control with state dependent fractional brownian noise and stochastic coefficients*, IFAC-PapersOnLine, 50(2): 199-202, 2017.

Original LQR papers



## Nonlinear systems:

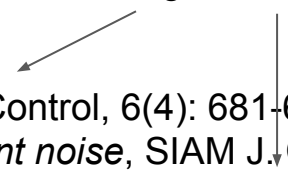
- A. Meshab, S. Streif, R. Findeisen, R.D. Braatz, *Stochastic nonlinear model predictive control with probabilistic constraints*, American Control Conference, 2014, Portland (Oregon).
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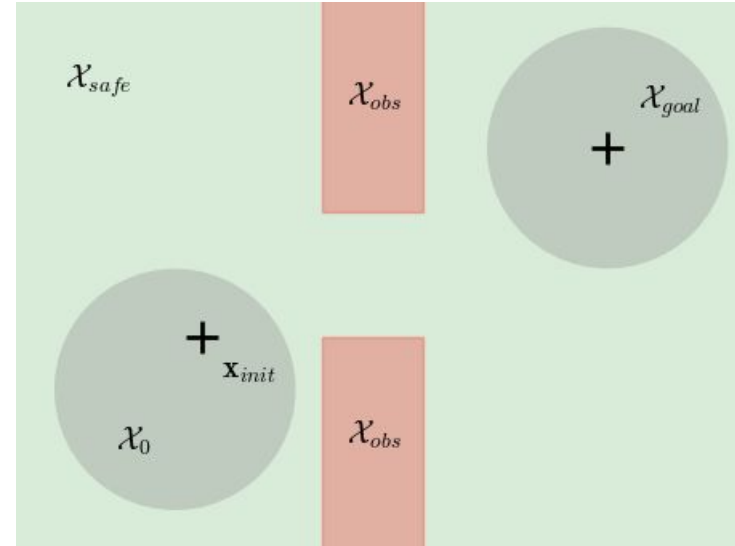
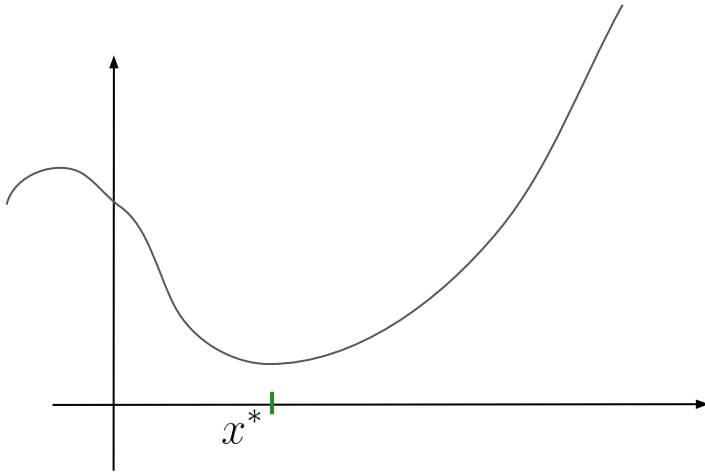


Remark  
Leverage existing works on linear systems: **Sequential Convex Programming (SCP)**

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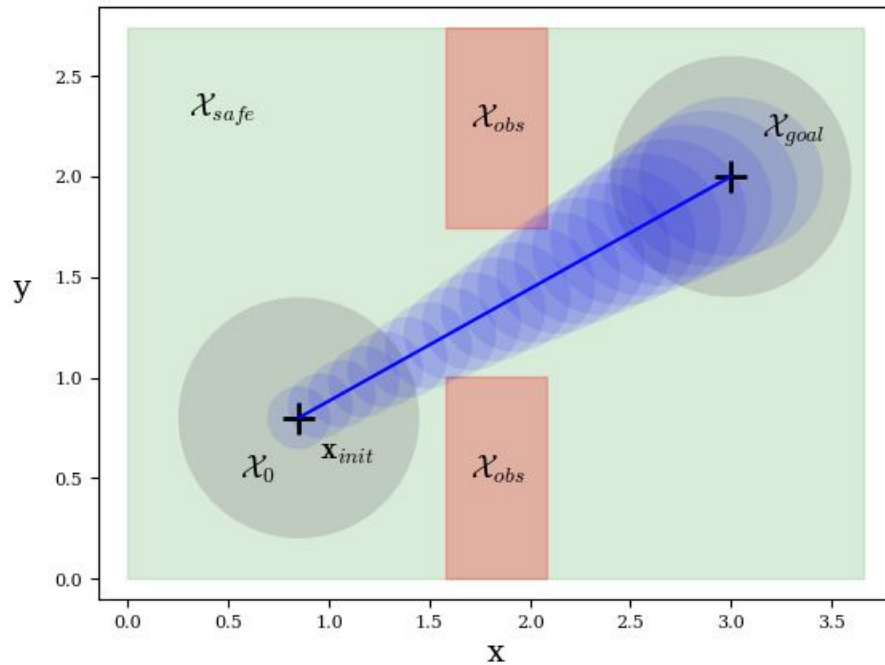
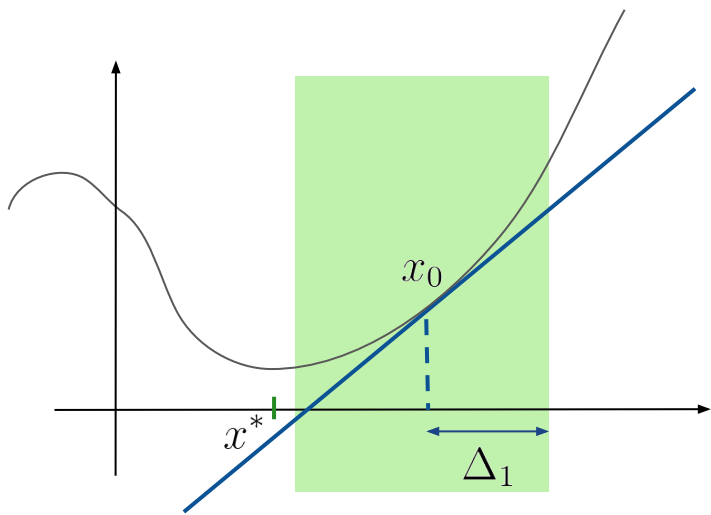
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# Intuitive introduction to SCP

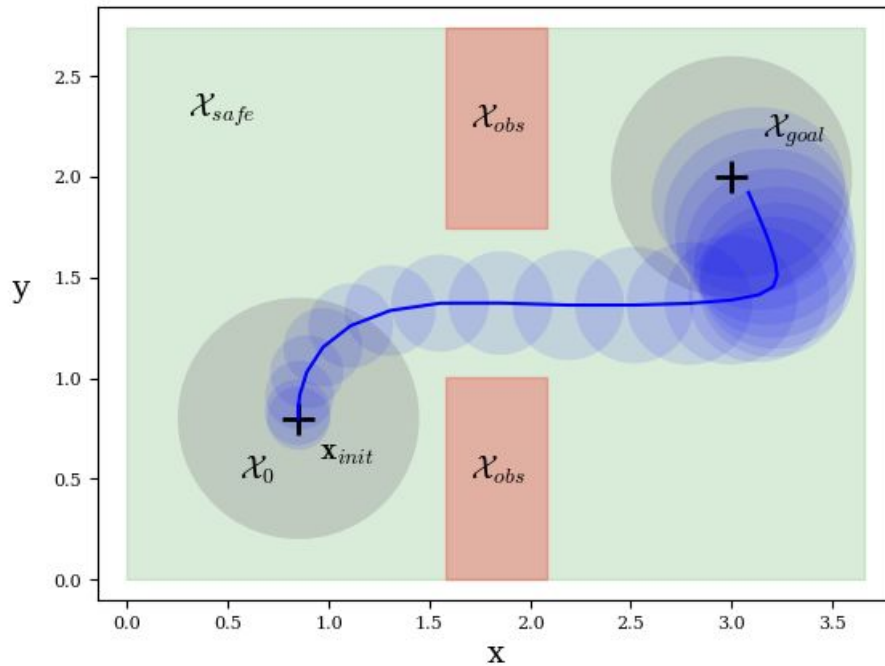
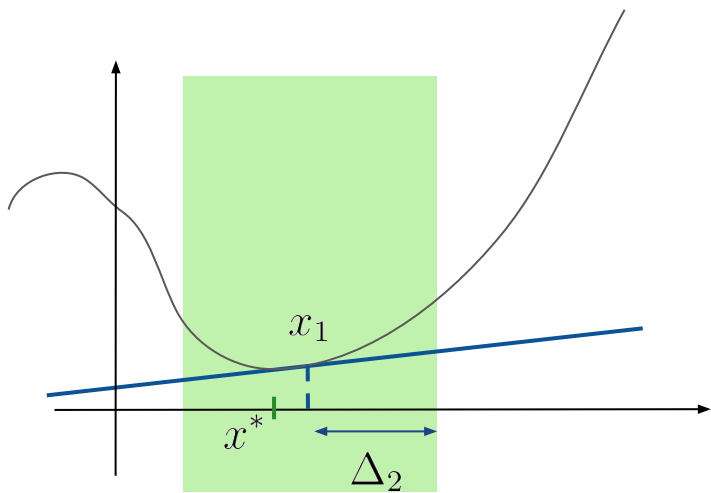




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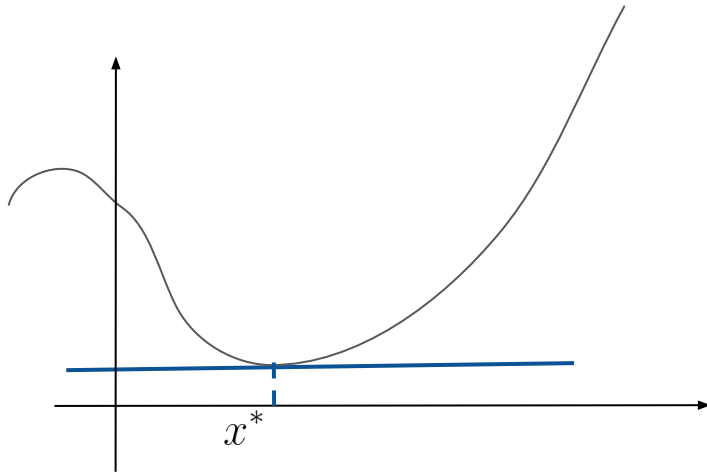


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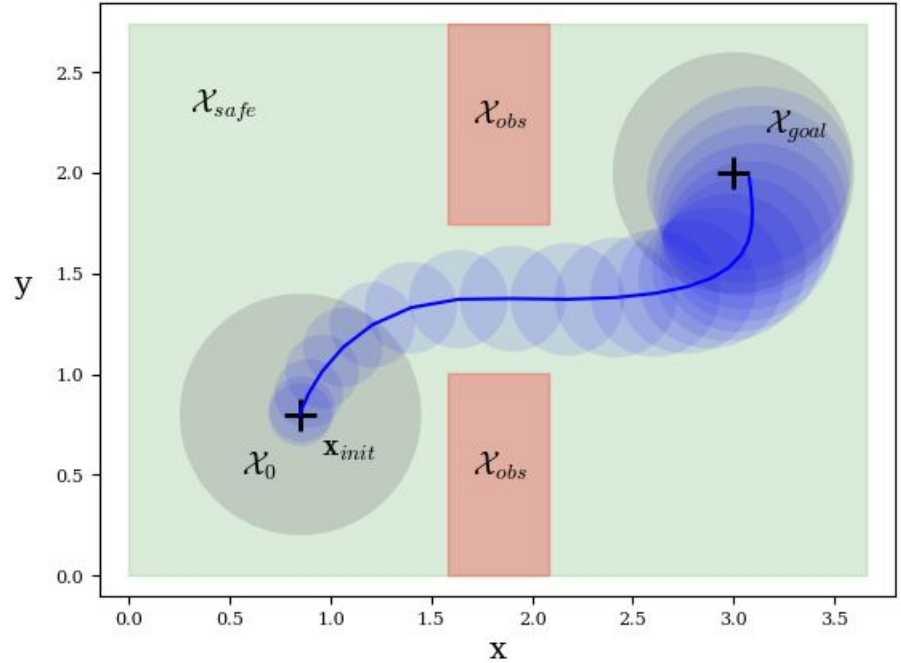


# Intuitive introduction to SCP

A few iterations later...



Convergence!



# Stochastic SCP formulation

$$\begin{aligned} & \min_{u \in \mathcal{U}} \mathbb{E} \left[ \int_0^{t_f} u(s)^2 + h(x(s)) \, ds \right] \\ \text{(OCP)} \quad & dx(s) = b(x(s), u(s)) \, ds + \sigma(x(s)) \, dB_s \\ & \triangleq (f_0(x(s)) + u(s)f_1(x(s))) \, ds + \sigma(x(s)) \, dB_s \\ & x(0) = x^0, \quad \mathbb{E}[g(x(t_f))] = 0 \end{aligned}$$

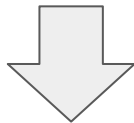
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$$(\mathbf{OCP}) \quad dx(s) = b(x(s), u(s)) \, ds + \sigma(x(s)) \, dB_s$$

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$$\min_{u \in \mathcal{U}} \mathbb{E} \left[ \int_0^{t_f} u(s)^2 + h(x_k(s)) + \frac{\partial h}{\partial x}(x_k(s))(x(s) - x_k(s)) \, ds \right]$$

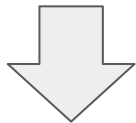
$$dx(s) = \left( b(x_k(s), u(s)) + \frac{\partial b}{\partial x}(x_k(s), u_k(s))(x(s) - x_k(s)) \right) ds$$

$$(\mathbf{COCP})_{k+1} + \left( \sigma(x_k(s)) + \frac{\partial \sigma}{\partial x}(x_k(s))(x(s) - x_k(s)) \right) dB_s$$

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 \end{aligned}$$

Linearization makes sense only locally.  
Add **trust-region constraints**:

$$\begin{aligned}
 & \mathbb{E} \left[ \int_0^{t_f} \|x(s) - x_k(s)\|^2 \, ds \right] \leq \Delta_{k+1} \\
 & \Delta_{k+1} \in \mathbb{R}_+, \quad \Delta_{k+1} \rightarrow 0
 \end{aligned}$$

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This begs the question: “Are we doing something meaningful? I.e., when convergence is achieved, what is the quantity we come up with?”

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Under mild assumptions, SCP finds a local optimum for (OCP), in the sense of the Pontryagin Maximum Principle (PMP)



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Under mild assumptions, SCP finds a local optimum for (OCP), in the sense of the Pontryagin Maximum Principle (PMP)

The proof leverages the **continuity** properties of stochastic Itô variational inequalities with respect to **convexification**

# The stochastic Pontryagin Maximum Principle

Let  $\mathcal{U} = L^2([0, t_f]; U)$  or  $\mathcal{U} = L^2([0, t_f] \times \Omega; U)$ , where  $U \subseteq \mathbb{R}$ . For **(OCP)**, we define the Hamiltonian

$$H(x, p, p^0, q, u) = p^\top (f_0(x) + u f_1(x)) + p^0 (u^2 + h(x)) + q^\top \sigma(x).$$

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$$dx(s) = \frac{\partial H}{\partial p}(x(s), p(s), p^0, q(s), u(s)) ds + \sigma(x(s)) dB_s,$$

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- **Maximality Condition:**

Deterministic controls:  $\mathbb{E} [H(x(s), p(s), p^0, q(s), u(s))] = \max_{u \in U} \mathbb{E} [H(x(s), p(s), p^0, q(s), u)], \quad \text{a.e.}$

Stochastic controls:  $H(x(s), p(s), p^0, q(s), u(s)) = \max_{u \in U} H(x(s), p(s), p^0, q(s), u), \quad \text{a.e. a.s.}$

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- **Transversality Condition:**  $p(t_f) \perp \ker \mathbb{E} \left[ \frac{\partial g}{\partial x}(x(t_f)) \right].$

# Theoretical guarantees for stochastic SCP

Assume that SCP provides a sequence  $(\Delta_k, u_k, x_k)_{k \in \mathbb{N}}$  such that:

- $(u_k(\cdot), x_k(\cdot))$  locally solves  $(\mathbf{COCP})_k$ ;
- $\mathbb{E} \left[ \int_0^{t_f} \|x_{k+1}(s) - x_k(s)\|^2 ds \right] < \Delta_{k+1}$  where  $\Delta_k \rightarrow 0$ ;
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Main result of convergence

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1. There exists  $(p(\cdot), p^0, q(\cdot))$  such that  $(x(\cdot), p(\cdot), p^0, q(\cdot), u(\cdot))$  is a Pontryagin extremal for  $(\mathbf{OCP})$ ;
2. Whenever  $k \rightarrow \infty$ , the following convergences hold:

$$(a) \mathbb{E} \left[ \sup_{s \in [0, t_f]} \|x_k(s) - x(s)\|^2 \right] \rightarrow 0$$

$$(b) p_k^0 \rightarrow p^0, \mathbb{E} \left[ \sup_{s \in [0, t_f]} \|p_k(s) - p(s)\|^2 \right] \rightarrow 0, \mathbb{E} \left[ \int_0^{t_f} \|q_k(s) - q(s)\|^2 ds \right] \rightarrow 0, \text{ up to a subsequence}$$

where  $(x_k(\cdot), p_k(\cdot), p_k^0, q_k(\cdot), u_k(\cdot))$  is a Pontryagin extremal for  $(\mathbf{COCP})_k$ .

It may be relaxed by using final constraints

We may adopt weak convergences for deterministic controls

Main result of convergence

Note: this may be leveraged to accelerate SCP!

# Convergence of SCP: sketch of proof

Define the augmented dynamics to be

$$\tilde{b}(x, u) = (f_0(x) + uf_1(x), u^2 + h(x)) \in \mathbb{R}^{n+1}, \quad \tilde{\sigma}(x) = (\sigma(x), 0) \in \mathbb{R}^{n+1}.$$

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To prove the PMP, we can leverage classical **needle-like variations** on the end-point mapping

$$E : \mathcal{U} \longrightarrow \mathbb{R}^{n+1} : u(\cdot) \mapsto \left( \mathbb{E} [g(x_u(t_f))], \mathbb{E} [x_u^{n+1}(t_f)] \right), \quad \begin{cases} d\tilde{x}_u(s) = \tilde{b}(x_u(s), u(s)) ds + \tilde{\sigma}(x_u(s)) dB_s \\ x_u(0) = x^0, \quad x_u^{n+1}(0) = 0. \end{cases}$$

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$$\tilde{b}(x, u) = (f_0(x) + uf_1(x), u^2 + h(x)) \in \mathbb{R}^{n+1}, \quad \tilde{\sigma}(x) = (\sigma(x), 0) \in \mathbb{R}^{n+1}.$$

To prove the PMP, we can leverage classical **needle-like variations** on the end-point mapping

$$E : \mathcal{U} \longrightarrow \mathbb{R}^{n+1} : u(\cdot) \mapsto \left( \mathbb{E} [g(x_u(t_f))], \mathbb{E} [x_u^{n+1}(t_f)] \right), \quad \begin{cases} d\tilde{x}_u(s) = \tilde{b}(x_u(s), u(s)) ds + \tilde{\sigma}(x_u(s)) dB_s \\ x_u(0) = x^0, \quad x_u^{n+1}(0) = 0. \end{cases}$$

If  $(u(\cdot), x(\cdot))$  is optimal, a contradiction argument entails the existence of  $(\mathbf{p}, p^0) \neq 0$  such that

$$\mathbf{p}^\top \mathbb{E} \left[ \frac{\partial g}{\partial x}(x(t_f)) z_{r,v}(t_f) \right] + p^0 \mathbb{E} [z_{r,v}^{n+1}(t_f)] \leq 0, \quad r \text{ Lebesgue point for } u(\cdot), \quad v \in L^2_{\mathcal{F}_r}(\Omega; U)$$

where  $\tilde{z}_{r,v} = (z_{r,v}, z_{r,v}^{n+1}) : [0, t_f] \times \Omega \rightarrow \mathbb{R}^{n+1}$  solves

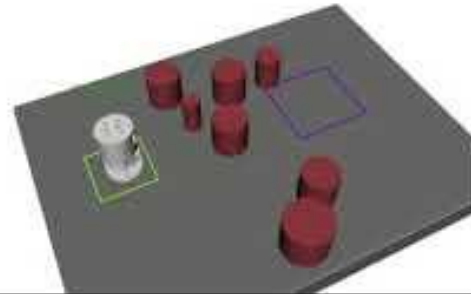
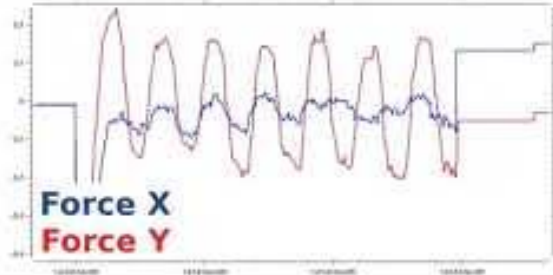
$$\begin{cases} d\tilde{z}(s) = A(s)\tilde{z}(s) ds + D(s)\tilde{z}(s) dB_s \\ \tilde{z}(s) = 0, \quad s \in [0, r), \quad \tilde{z}(r) = \tilde{b}(x(r), v) - \tilde{b}(x(r), u(r)), \end{cases} \quad \begin{cases} A(s) = \frac{\partial \tilde{b}}{\partial \tilde{x}}(x(s), u(s)) \\ D(s) = \frac{\partial \tilde{\sigma}}{\partial \tilde{x}}(x(s), u(s)). \end{cases}$$

Lebesgue points for stochastic controls are correctly introduced via Bochner integration

# Hardware exp. - Collaboration with Stanford University



Explore & learn  
inertial properties





# Future direction

Solve non-linear coupled ODEs/PDEs

FEM+ROM tend to lose effectiveness

$$\left\{ \begin{array}{l} \min_{u \in \mathcal{U}} \int_0^{t_f} \|u(t)\|^2 dt \\ dx = f(x, y, u) dt + \sigma(x, y, u) dB_t \\ \frac{\partial y}{\partial t} - \mu \Delta y + \nabla p = -y \cdot \nabla y \end{array} \right.$$

# Future direction

Solve non-linear coupled ODEs/PDEs

FEM+ROM tend to lose effectiveness

Could we extend the performance of SCP?

$$\left\{ \begin{array}{l} \min_{u \in \mathcal{U}} \int_0^{t_f} \|u(t)\|^2 dt \\ dx = f(x, y, u) dt + \sigma(x, y, u) dB_t \\ \frac{\partial y}{\partial t} - \mu \Delta y + \nabla p = -y \cdot \nabla y \end{array} \right. \implies \left\{ \begin{array}{l} \min_{u_{k+1} \in \mathcal{U}} \int_0^{t_f} \|u_{k+1}(t)\|^2 dt \\ \dots \\ \frac{\partial y^{k+1}}{\partial t} - \mu \Delta y^{k+1} + \nabla p^{k+1} = \\ = -y^k \cdot \nabla y^k - (y^{k+1} - y^k) \cdot \nabla y^k + \text{“trust region” constraints} \\ -y^k \cdot \nabla (y^{k+1} - y^k) \end{array} \right.$$

# Future direction

Solve non-linear coupled ODEs/PDEs

FEM+ROM tend to lose effectiveness

Could we extend the performance of SCP?

Thank you for your attention!  
Any question?

$$\left\{ \begin{array}{l} \min_{u \in \mathcal{U}} \int_0^{t_f} \|u(t)\| \\ dx = f(x, y, u) dt + \sigma(x, y) \\ \frac{\partial y}{\partial t} - \mu \Delta y + \nabla p = -y \cdot \nabla y \end{array} \right.$$

$$= -y^k \cdot \nabla y^k - (y^{k+1} - y^k) \cdot \nabla y^k + \text{“trust region” constraints} \\ -y^k \cdot \nabla (y^{k+1} - y^k)$$

## References

- [1] R. Bonalli, T. Lew, and M. Pavone, *Sequential Convex Programming for Non-Linear Stochastic Optimal Control*. Submitted.
- [2] R. Bonalli and Y. Chitour, *Sequential Convex Programming for Infinite Dimensional Non-Linear Optimal Control*. In progress.