

# Recent Advances in Estimation, Safety, and Control

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# Outline of Recent Results

## 1. Estimation

- ▶ Parameter Estimation via Hybrid Methods  
*ACC 21a, ACC 21b, ACC 21c, CDC 22a (submitted)*
- ▶ Observers for Hybrid Systems  
*CDC 21a, CDC 21b, Automatica 22 (to appear)*

## 2. Safety

- ▶ Safety Certificates  
*ACC 22a, TAC 22, ESAIM 22 + CoE collab*
- ▶ Applications of Safety  
*ACC 22b, CCTA 22a and CCTA 22b (submitted) + CoE collab*

## 3. Feedback Control and Optimization

- ▶ Hybrid Control and Learning  
*ACC 22c, ACC 22d, CCTA 22a (submitted), CDC 22b (submitted)*
- ▶ Optimization with Computational Constraints  
*CPSWeek-IoT 22 Workshop + AFRL/RV collab + CoE collab.*



# Questions Driving Research Agenda

These observations motivate the following questions:

- ▶ How to guarantee the monotonicity condition

$$t \mapsto B(\phi(t; x_o)) \text{ is nonincreasing}$$

and

$$\text{the set } K_e \text{ is "forward invariant" for } \dot{x} = f(x)$$

without checking/computing every solution?

- ▶ How to deal with nonuniqueness, finite escape time, and solutions ending prematurely?
- ▶ What are necessary conditions for safety (and invariance)?

... for dynamical systems given by

$$\mathcal{H} \quad \begin{cases} \dot{x} & \in F(x) & x \in C \\ x^+ & \in G(x) & x \in D \end{cases}$$



# Basic Definitions

- ▶ When  $B$  is **continuously differentiable**, our sufficient conditions take the form

$$\langle \nabla B(x), F(x) \rangle \leq 0$$

Note that since invariance should just guarantee **trajectories do not leave a set**, we should only be asking that this condition holds on the boundary or a neighborhood of the set.

Hence, we require

$$\langle \nabla B(x), f(x) \rangle \leq 0 \quad \forall x \in (U(\partial K_e) \setminus K_e)$$

where  $U(\partial K_e)$  is a neighborhood of  $K_e$ , so  $(U(\partial K_e) \setminus K_e)$  are points outside right outside  $K_e$ !

# Sampling-based safety of constrained control system

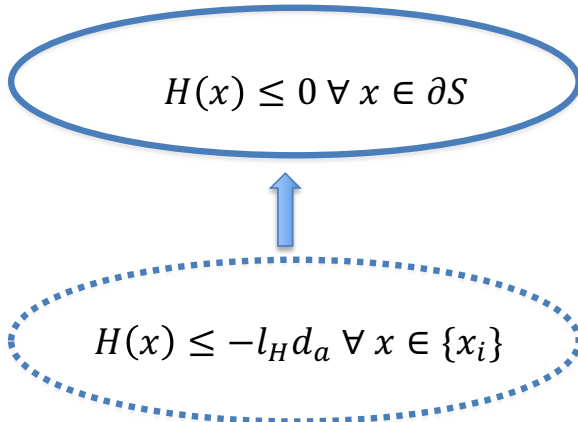
Consider the dynamical control system:

$$\dot{x} = F(x, u), \quad x(0) \in S = \{x \mid B(x) \leq 0\}, u \in \mathcal{U}$$

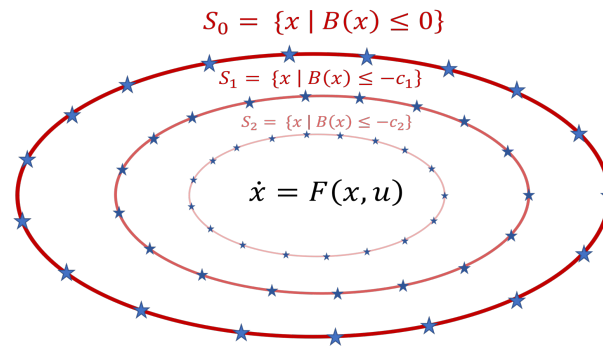
Joint work with Kunal Garg and Alvaro Cardenas

$$H(x) := \inf_{u \in \mathcal{U}} \{L_F B(x, u)\} \leq 0 \quad \forall x \in \partial S \Rightarrow \text{Forward invariance of } S$$

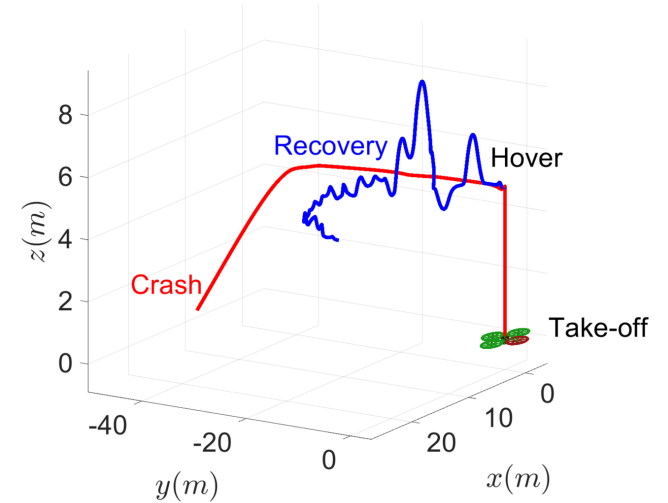
Infeasible to verify:  $\partial S$   
contains infinite points



Computationally efficient and  
scalable to higher dimensions



Iterative method to  
compute viability domain



CBF-based attack detection and  
recovery with provable safety

Garg, K., Cardenas, A.A., Sanfelice, R.G., "Sampling-based Computation of Viability Domain to Prevent Safety Violations by Attackers", under review.

Garg, K., Sanfelice, R.G., Cardenas, A.A., "Control barrier function based attack-recovery with provable guarantees", under review.

Constrained control with provable guarantees

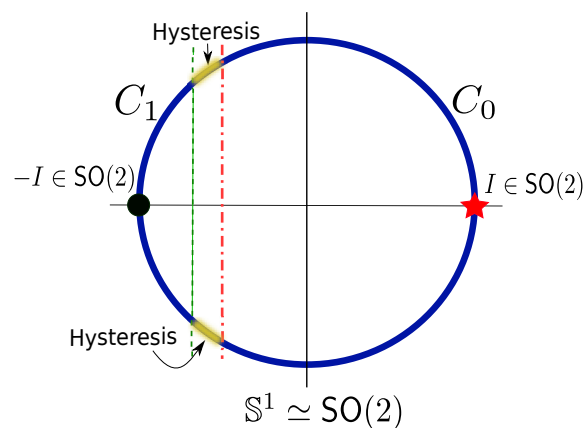
# Hybrid Geometric Controls

- System on Lie groups

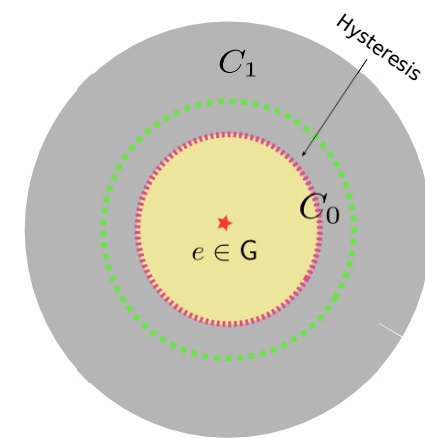
joint work with Adeel Akhtar

$$\dot{g} = X(g, u) = g \left( A + \sum_{i=1}^m B_i u_i \right) = g\xi,$$

- ▶ Region  $C_0$  containing the identity.
- ▶ Region  $C_1$  containing all other critical points.
- Hybrid Controls
  - ▶ Design an asymptotically stable geometric controller  $\kappa_0$  and an open loop geometric controller  $\kappa_1$  and combine them using hybrid framework.
  - ▶ Hysteresis region leads to robustness.
  - ▶ The resulting hybrid controller is robust.



Global Stabilization

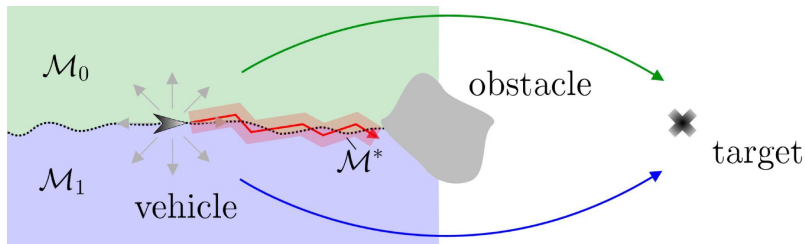


Matrix Lie groups

# Hysteresis-based Reinforcement Learning (HyRL):

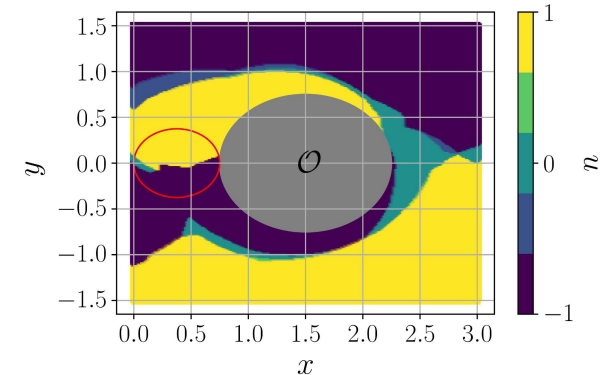


*Robustifying Reinforcement Learning-based Control Policies via Hybrid Control.*

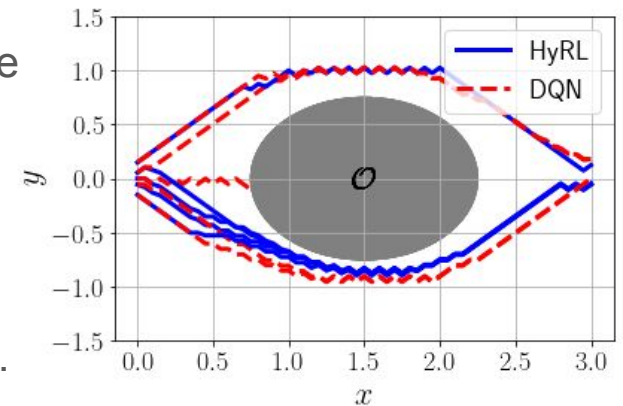


*Autonomous vehicle obstacle avoidance. The vehicle has to steer left or right past the obstacle. In red, the area for which, due to measurement noise, the vehicle can crash into the obstacle.*

- Policies obtained from RL methods may lack robustness guarantees.
  - Solutions evolve in opposite directions for a small change in the state.
- HyRL overcomes this by augmenting an existing RL algorithm with hysteresis switching and two stages of learning.
  - The hybrid closed-loop system obtained by HyRL is robust against measurement noise of a given magnitude.



*The policy found by DQN: solutions evolve in opposite directions for a small change in  $y$ .*

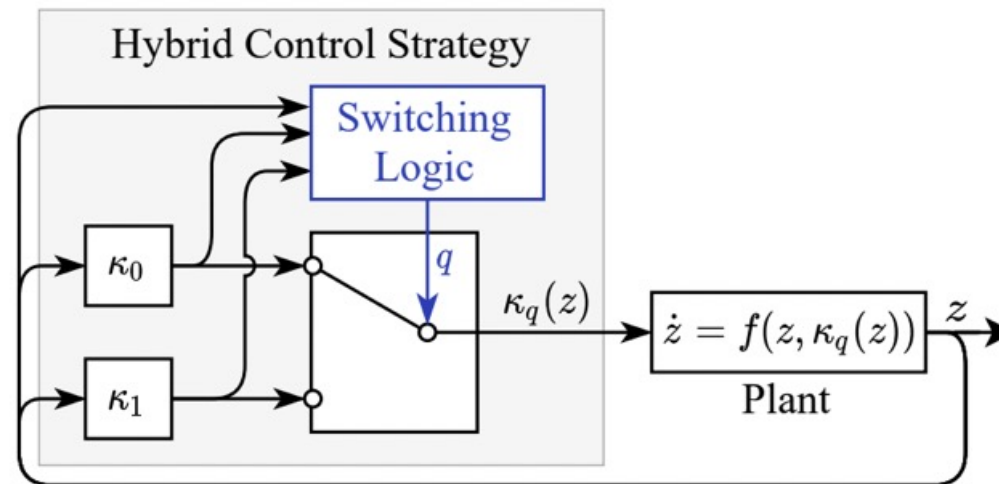


*DQN and HyRL solutions in the presence of the same measurement noise signal of magnitude 0.1. The DQN policy is not robust against the measurement noise, unlike HyRL.*

joint work with Jan de Priester and Nathan van de Wouw

J. de Priester, R. G. Sanfelice, N. van de Wouw, "Hysteresis-Based RL: Robustifying Reinforcement Learning-based Control Policies via Hybrid Control", To appear in the Proceedings of the American Control Conference, June, 2022. Available at <https://arxiv.org/abs/2204.00654>.

# Opportunistic Hybrid Control Exploiting Properties of **Uncertified** Controller

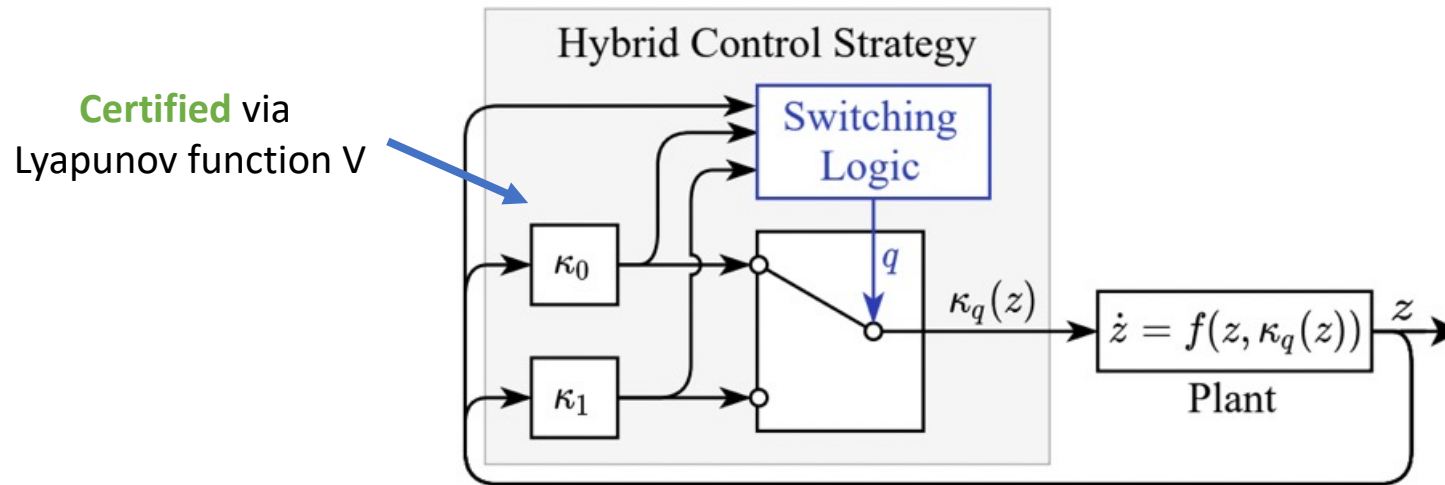


joint work with Paul Wintz and Joao Hespanha

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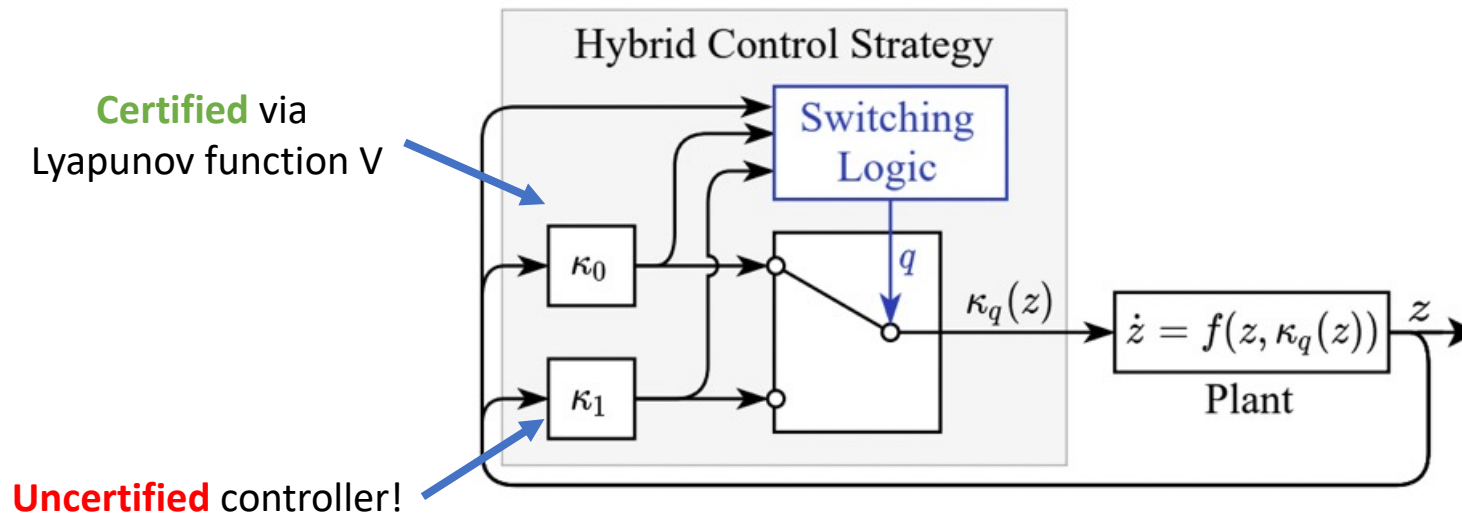
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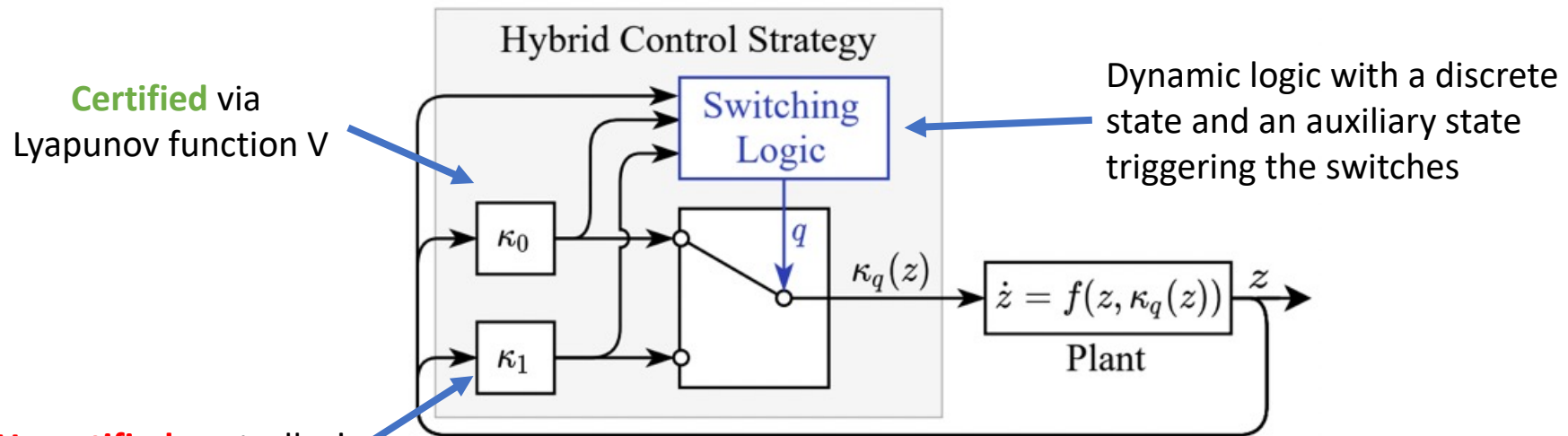


- Heuristics
- Online optimization-based feedback
- NN-based controller
- ...

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# Opportunistic Hybrid Control Exploiting Properties of **Uncertified** Controller



**Uncertified** controller!

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- Online optimization-based feedback
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