

Adaptive Safety with Control Barrier Functions

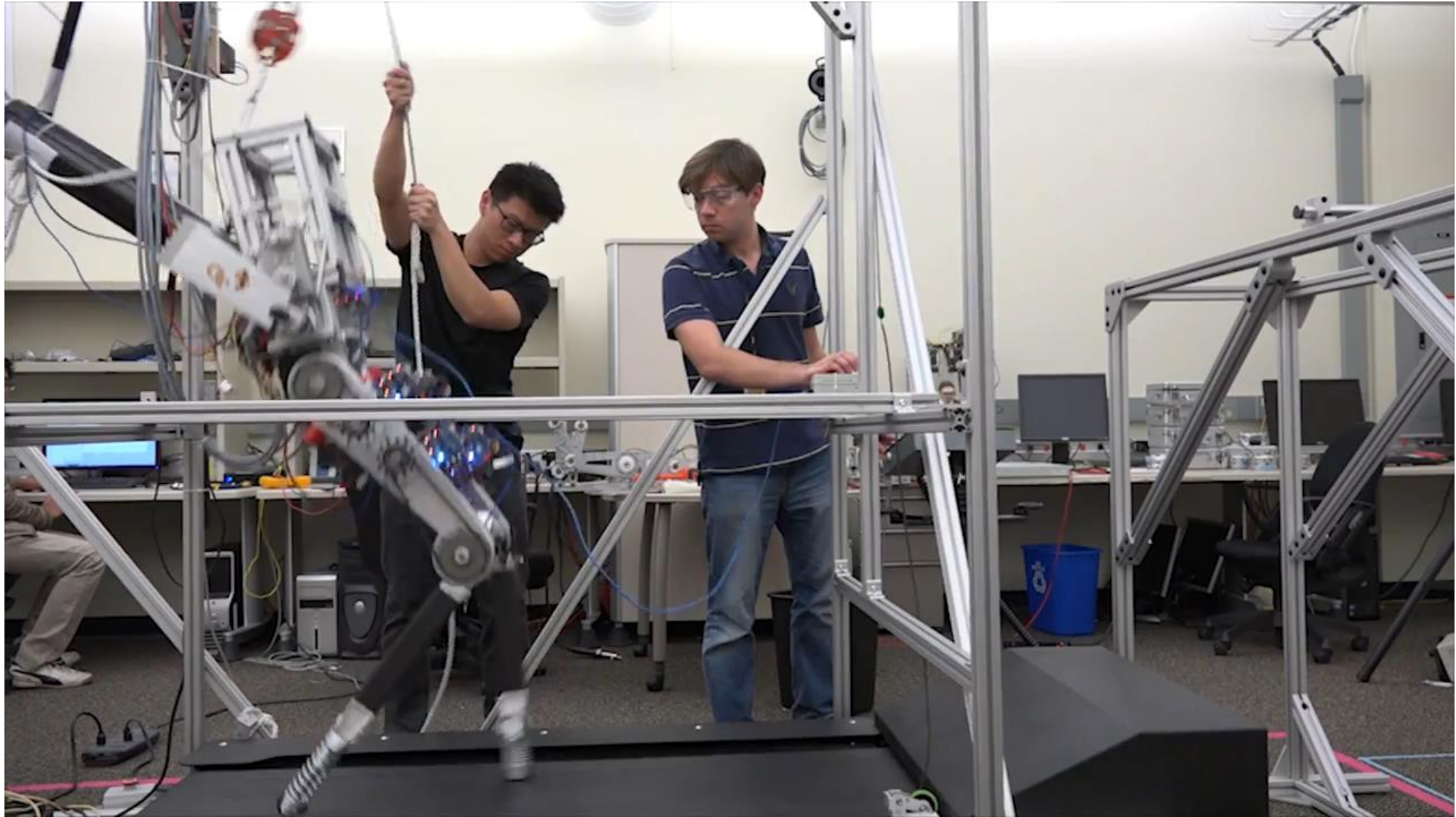
Andrew Taylor Aaron Ames

Computing and Mathematical Sciences
California Institute of Technology

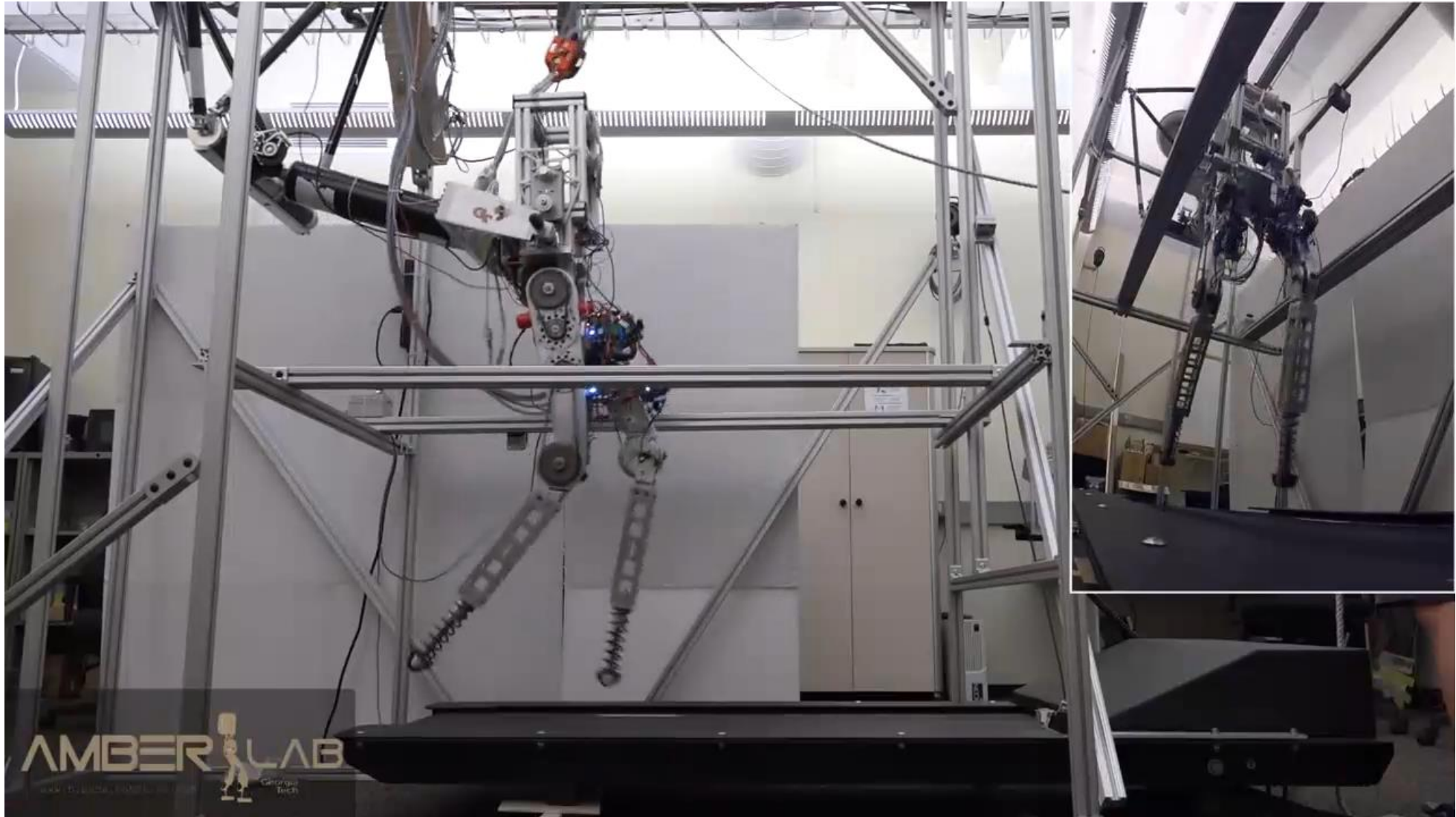
July 1st, 2020

American Control Conference 2020

Control in the real world is hard

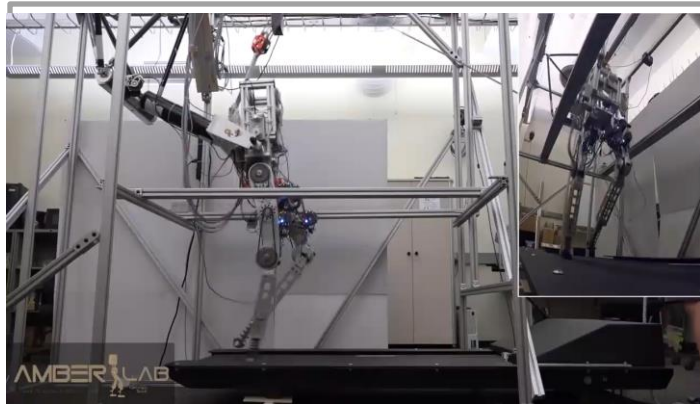


But: Pretty when it works...



[1] W. Ma, et al., Bipedal robotic running with durus-2d: Bridging the gap between theory and experiment

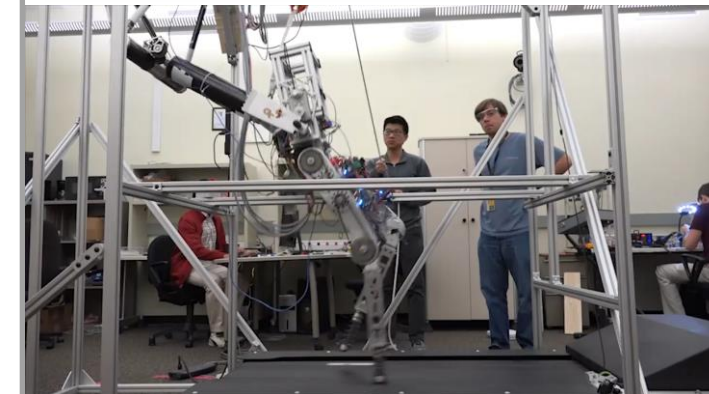
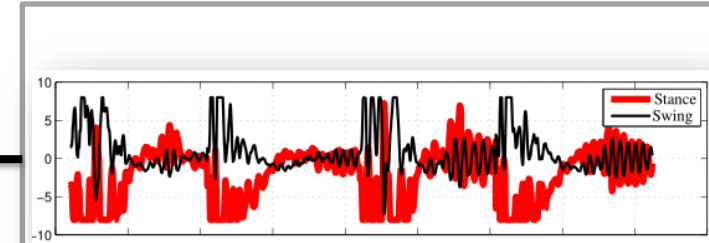
Claim: Need to Bridge the Gap



$$\mathbf{k}(\mathbf{x}) = \operatorname{argmin}_{\mathbf{u} \in \mathbb{R}^m} \|\mathbf{u}\|_2^2$$
$$\text{s.t. } \dot{h}(\mathbf{x}, \mathbf{u}) \geq -\alpha(h(\mathbf{x}))$$

Theorems & Proofs

Bridge the
Gap



Experimental Realization

- Framework for achieving safety of uncertain systems via **Adaptive Control Barrier Functions (aCBFs)**
- Analysis of the conservative nature of the aCBF conditions through a pathological example
- Combination of adaptive control methods for stabilization and safety demonstrated on an Adaptive Cruise Control system

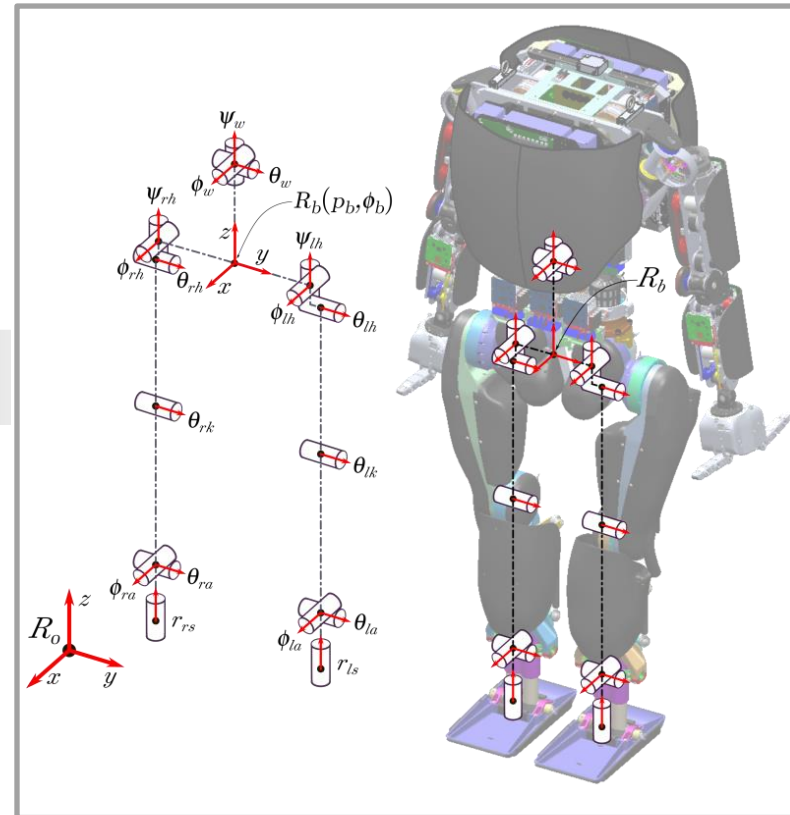
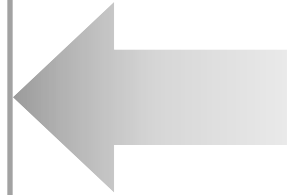
Equations of Motion

$$\hat{\dot{\mathbf{x}}} = \mathbf{f}(\mathbf{x}) + \mathbf{g}(\mathbf{x})\mathbf{u}$$

$$\mathbf{x} \in \mathbb{R}^n \quad \mathbf{u} \in \mathbb{R}^m$$

$$\mathbf{f} : \mathbb{R}^n \rightarrow \mathbb{R}^n \quad \mathbf{g} : \mathbb{R}^n \rightarrow \mathbb{R}^{n \times m}$$

Mathematical Model



System Model

Equations of Motion

$$\hat{\dot{\mathbf{x}}} = \mathbf{f}(\mathbf{x}) + \mathbf{g}(\mathbf{x})\mathbf{u}$$

$$\mathbf{x} \in \mathbb{R}^n \quad \mathbf{u} \in \mathbb{R}^m$$

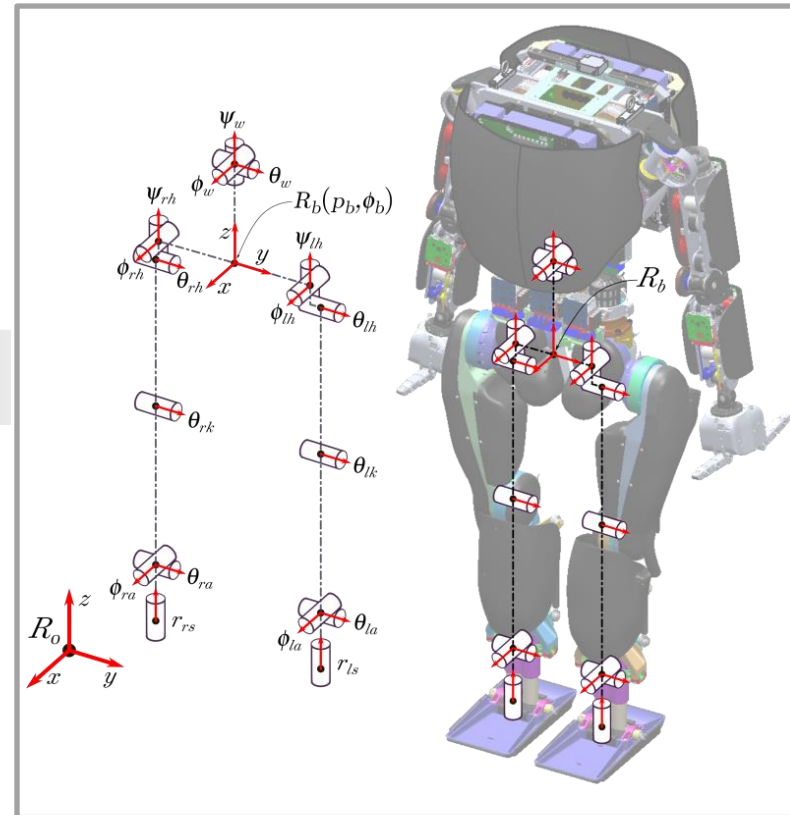
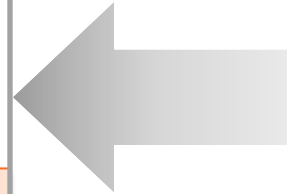
$$\mathbf{f} : \mathbb{R}^n \rightarrow \mathbb{R}^n \quad \mathbf{g} : \mathbb{R}^n \rightarrow \mathbb{R}^{n \times m}$$

Assumptions

\mathbf{f}, \mathbf{g} locally Lipschitz continuous

$$\mathbf{f}(\mathbf{0}) = \mathbf{0}$$

Mathematical Model



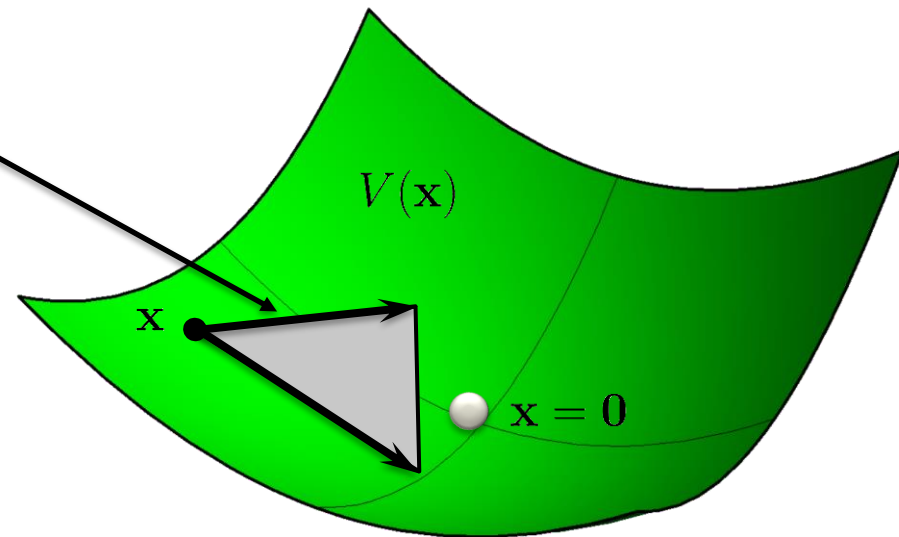
System Model

Control Lyapunov Function

$$\alpha_1 (\|\mathbf{x}\|_2) \leq V(\mathbf{x}) \leq \alpha_2 (\|\mathbf{x}\|_2)$$

$$\inf_{\mathbf{u} \in \mathbb{R}^m} \dot{V}(\mathbf{x}, \mathbf{u}) \leq -\alpha_3 (\|\mathbf{x}\|_2)$$

$$\dot{V}(\mathbf{x}, \mathbf{u}) = \frac{\partial V}{\partial \mathbf{x}} (\mathbf{f}(\mathbf{x}) + \mathbf{g}(\mathbf{x})\mathbf{u})$$



Control Lyapunov Function

$$\alpha_1 (\|\mathbf{x}\|_2) \leq V(\mathbf{x}) \leq \alpha_2 (\|\mathbf{x}\|_2)$$

$$\inf_{\mathbf{u} \in \mathbb{R}^m} \dot{V}(\mathbf{x}, \mathbf{u}) \leq -\alpha_3 (\|\mathbf{x}\|_2)$$

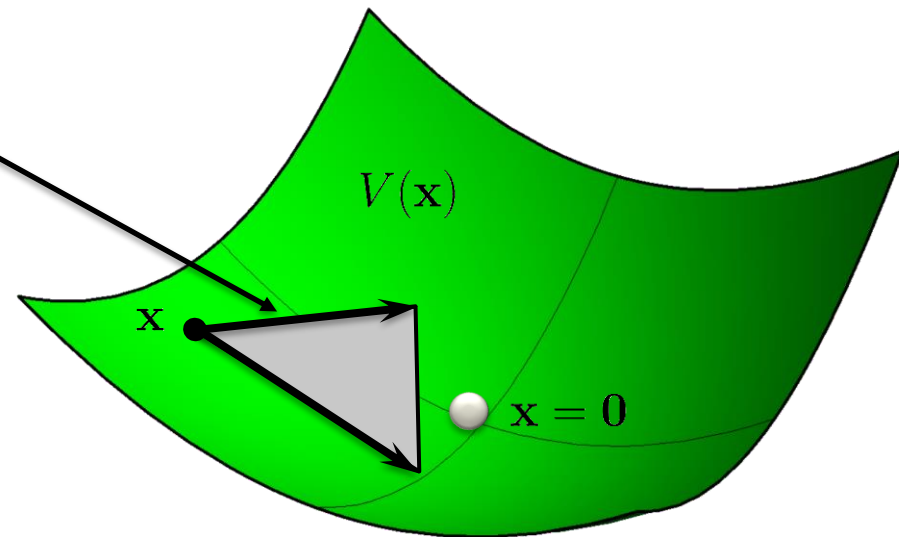
$$\dot{V}(\mathbf{x}, \mathbf{u}) = \frac{\partial V}{\partial \mathbf{x}} (\mathbf{f}(\mathbf{x}) + \mathbf{g}(\mathbf{x})\mathbf{u})$$

Feedback Controllers

[2] Z. Artstein, Stabilization with relaxed controls, 1983.

[3] E. Sontag, A universal construction of Artstein's theorem on nonlinear stabilization, 1989.

[4] R. Freeman, P. Kokotovic, Inverse Optimality in Robust Stabilization, 1996.



Control Lyapunov Function

$$\alpha_1 (\|\mathbf{x}\|_2) \leq V(\mathbf{x}) \leq \alpha_2 (\|\mathbf{x}\|_2)$$

$$\inf_{\mathbf{u} \in \mathbb{R}^m} \dot{V}(\mathbf{x}, \mathbf{u}) \leq -\alpha_3 (\|\mathbf{x}\|_2)$$

$$\dot{V}(\mathbf{x}, \mathbf{u}) = \frac{\partial V}{\partial \mathbf{x}} (\mathbf{f}(\mathbf{x}) + \mathbf{g}(\mathbf{x})\mathbf{u})$$

Feedback Controllers

[2] Z. Artstein, Stabilization with relaxed controls, 1983.

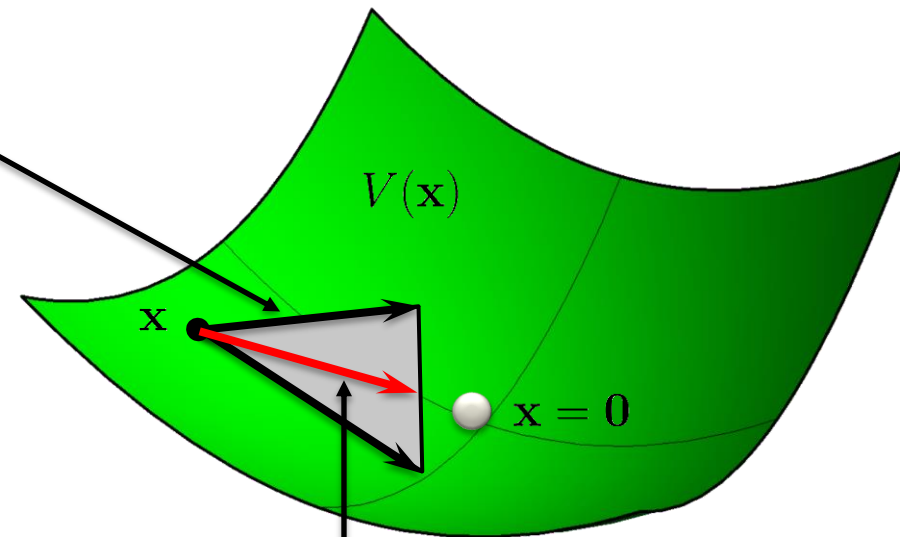
[3] E. Sontag, A universal construction of Artstein's theorem on nonlinear stabilization, 1989.

[4] R. Freeman, P. Kokotovic, Inverse Optimality in Robust Stabilization, 1996.

CLF Quadratic Program^[5]

$$\mathbf{k}(\mathbf{x}) = \operatorname{argmin}_{\mathbf{u} \in \mathbb{R}^m} \|\mathbf{u}\|_2$$

$$\text{s.t. } \dot{V}(\mathbf{x}, \mathbf{u}) \leq -\alpha_3 (\|\mathbf{x}\|_2)$$



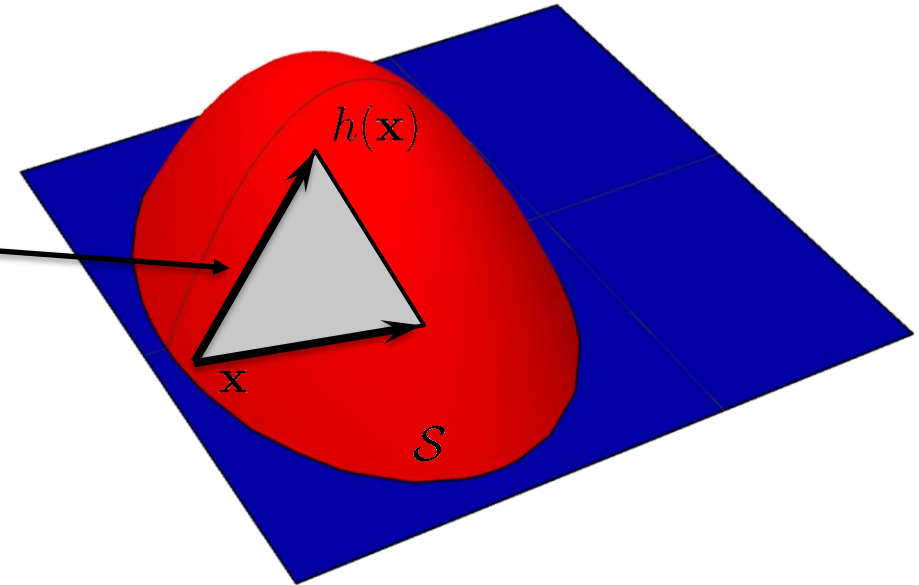
[5] A. Ames, M. Powell, Towards the unification of locomotion and manipulation through control lyapunov functions and quadratic programs.

Control Barrier Function

$$\mathcal{S} = \{\mathbf{x} \in \mathbb{R}^n \mid h(\mathbf{x}) \geq 0\}$$

$$\sup_{\mathbf{u} \in \mathbb{R}^m} \dot{h}(\mathbf{x}, \mathbf{u}) > -\alpha(h(\mathbf{x}))$$

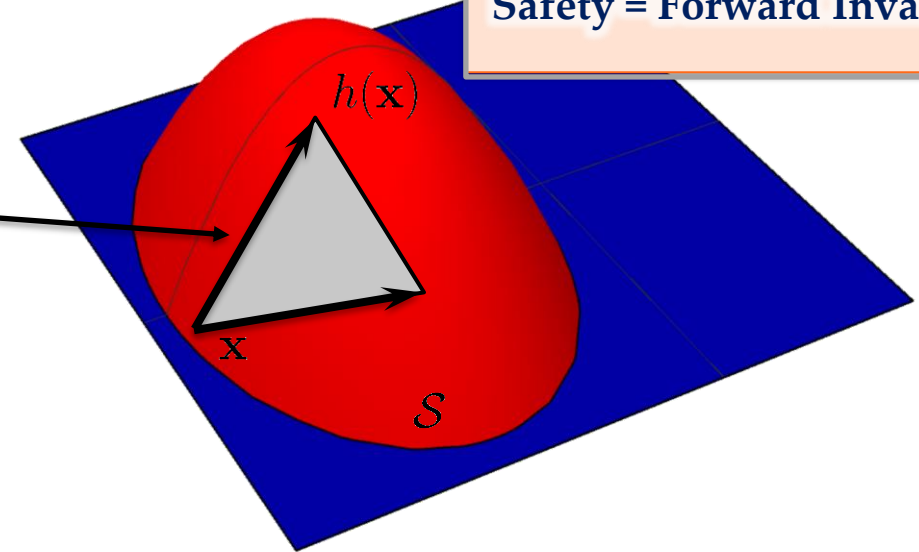
$$\dot{h}(\mathbf{x}, \mathbf{u}) = \frac{\partial h}{\partial \mathbf{x}} (\mathbf{f}(\mathbf{x}) + \mathbf{g}(\mathbf{x})\mathbf{u})$$



Control Barrier Function

$$\mathcal{S} = \{\mathbf{x} \in \mathbb{R}^n \mid h(\mathbf{x}) \geq 0\}$$
$$\sup_{\mathbf{u} \in \mathbb{R}^m} \dot{h}(\mathbf{x}, \mathbf{u}) > -\alpha(h(\mathbf{x}))$$
$$\dot{h}(\mathbf{x}, \mathbf{u}) = \frac{\partial h}{\partial \mathbf{x}} (\mathbf{f}(\mathbf{x}) + \mathbf{g}(\mathbf{x})\mathbf{u})$$

Safety = Forward Invariance



Control Barrier Function

$$\mathcal{S} = \{\mathbf{x} \in \mathbb{R}^n \mid h(\mathbf{x}) \geq 0\}$$

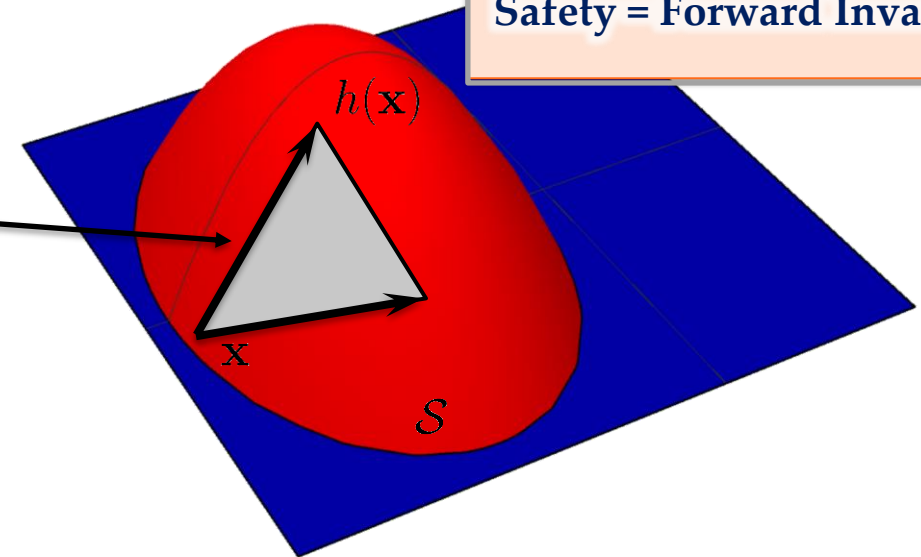
$$\sup_{\mathbf{u} \in \mathbb{R}^m} \dot{h}(\mathbf{x}, \mathbf{u}) > -\alpha(h(\mathbf{x}))$$

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

Feedback Controllers

- [6] A. Ames, et al. Control barrier function based quadratic programs with application to adaptive cruise control, 2014.
- [7] A. Ames, et al. Control barrier function based quadratic programs for safety critical systems, 2017.

Safety = Forward Invariance



Control Barrier Function

$$\mathcal{S} = \{\mathbf{x} \in \mathbb{R}^n \mid h(\mathbf{x}) \geq 0\}$$

$$\sup_{\mathbf{u} \in \mathbb{R}^m} \dot{h}(\mathbf{x}, \mathbf{u}) > -\alpha(h(\mathbf{x}))$$

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

Feedback Controllers

[6] A. Ames, et al. Control barrier function based quadratic programs with application to adaptive cruise control, 2014.

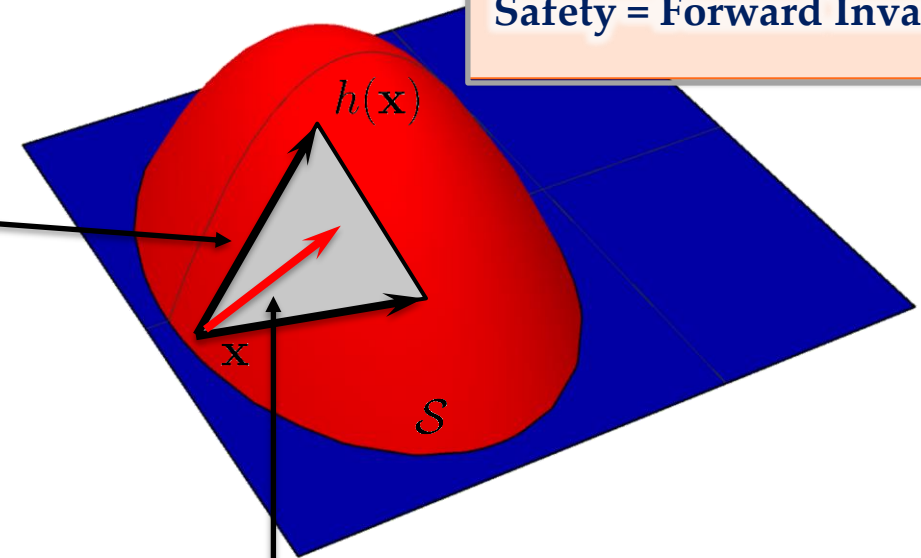
[7] A. Ames, et al. Control barrier function based quadratic programs for safety critical systems, 2017.

CBF Quadratic Program^[6]

$$\mathbf{k}(\mathbf{x}) = \operatorname{argmin}_{\mathbf{u} \in \mathbb{R}^m} \|\mathbf{u}\|_2^2$$

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

Safety = Forward Invariance



Control Barrier Function

$$\mathcal{S} = \{\mathbf{x} \in \mathbb{R}^n \mid h(\mathbf{x}) \geq 0\}$$

$$\sup_{\mathbf{u} \in \mathbb{R}^m} \dot{h}(\mathbf{x}, \mathbf{u}) > -\alpha(h(\mathbf{x}))$$

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

Feedback Controllers

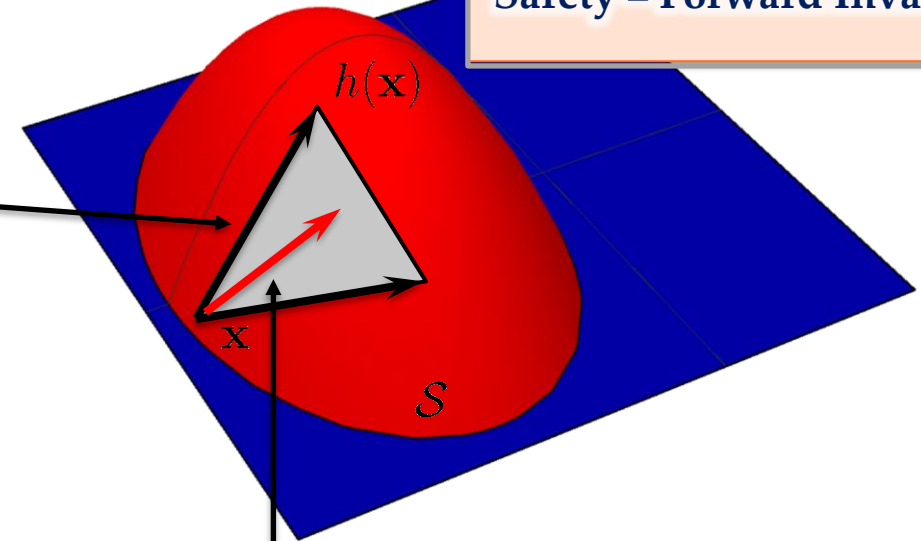
[6] A. Ames, et al. Control barrier function based quadratic programs with application to adaptive cruise control, 2014.
 [7] A. Ames, et al. Control barrier function based quadratic programs for safety critical systems, 2017.

CBF Quadratic Program^[6]

$$\mathbf{k}(\mathbf{x}) = \operatorname{argmin}_{\mathbf{u} \in \mathbb{R}^m} \|\mathbf{u}\|_2^2$$

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

Safety = Forward Invariance



CLF-CBF Quadratic Program^[8]

$$\mathbf{k}(\mathbf{x}) = \operatorname{argmin}_{(\mathbf{u}, \delta) \in \mathbb{R}^{m+1}} \|\mathbf{u}\|_2^2 + \delta^2$$

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

$$\dot{V}(\mathbf{x}, \mathbf{u}) \leq -\alpha_3(\|\mathbf{x}\|) + \delta$$

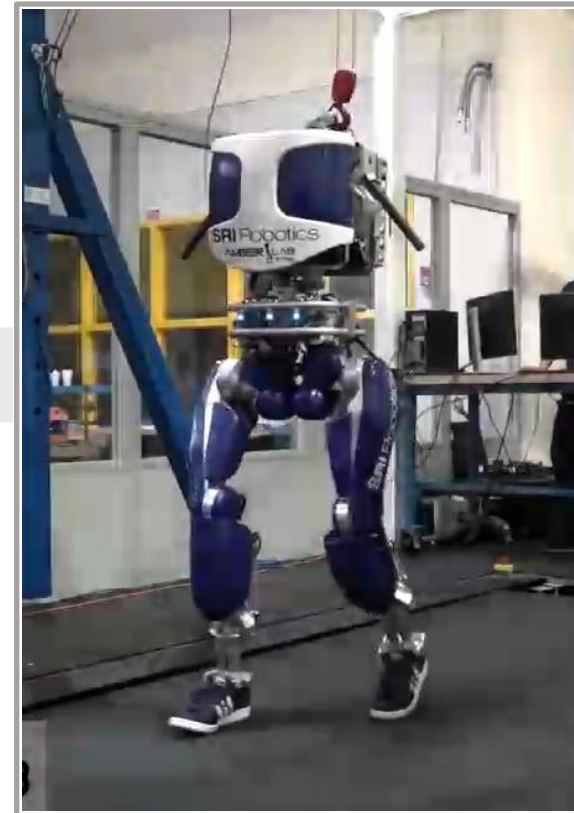
[8] M. Jankovic, Robust control barrier functions for constrained stabilization of nonlinear systems, 2018.

Equations of Motion

$$\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}) + \mathbf{F}(\mathbf{x})\boldsymbol{\theta}^* + \mathbf{g}(\mathbf{x})\mathbf{u}$$

$$\mathbf{F} : \mathbb{R}^n \rightarrow \mathbb{R}^{n \times p} \quad \boldsymbol{\theta}^* \in \mathbb{R}^p$$

True Dynamics



Physical System

Equations of Motion

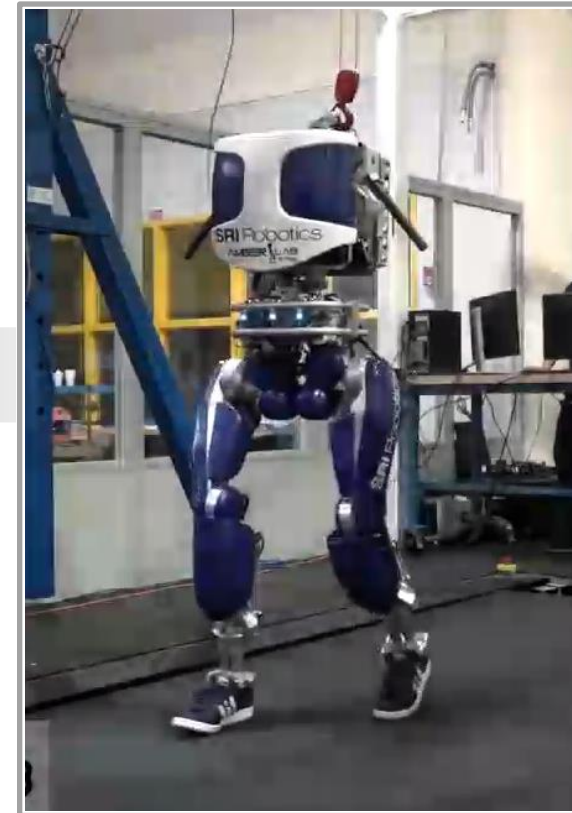
$$\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}) + \mathbf{F}(\mathbf{x})\boldsymbol{\theta}^* + \mathbf{g}(\mathbf{x})\mathbf{u}$$

$$\mathbf{F} : \mathbb{R}^n \rightarrow \mathbb{R}^{n \times p} \quad \boldsymbol{\theta}^* \in \mathbb{R}^p$$

Methods

- Adaptive Control^[9]
- System Identification^[10]
- Machine Learning^[11]
- High-gain control^[12]

True Dynamics



Physical System

[9] M. Krstic, et al., Nonlinear Adaptive Control Design

[10] L. Ljung, System Identification

[11] J. Kober, et al., Reinforcement learning in robotics: A survey

[12] A. Ilchmann, et al., High-gain control without identification: a survey

Equations of Motion

$$\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}) + \mathbf{F}(\mathbf{x})\boldsymbol{\theta}^* + \mathbf{g}(\mathbf{x})\mathbf{u}$$

$$\mathbf{F} : \mathbb{R}^n \rightarrow \mathbb{R}^{n \times p} \quad \boldsymbol{\theta}^* \in \mathbb{R}^p$$

Methods

- Adaptive Control^[9]
- System Identification^[10]
- Machine Learning^[11]
- High-gain control^[12]

True Dynamics



Physical System

[9] M. Krstic, et al., Nonlinear Adaptive Control Design

[10] L. Ljung, System Identification

[11] J. Kober, et al., Reinforcement learning in robotics: A survey

[12] A. Ilchmann, et al., High-gain control without identification: a survey

Equations of Motion

$$\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}) + \mathbf{F}(\mathbf{x})\boldsymbol{\theta}^* + \mathbf{g}(\mathbf{x})\mathbf{u}$$

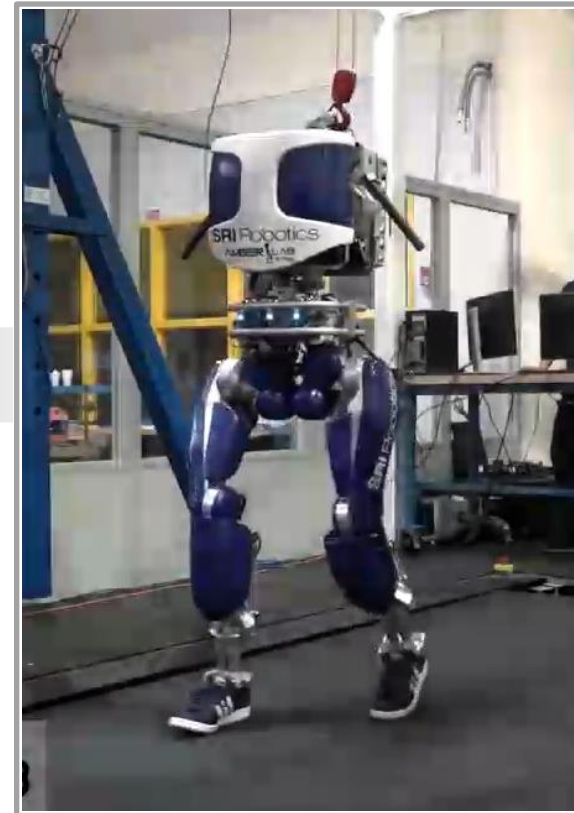
$$\mathbf{F} : \mathbb{R}^n \rightarrow \mathbb{R}^{n \times p} \quad \boldsymbol{\theta}^* \in \mathbb{R}^p$$

Assumptions

\mathbf{F} is locally Lipschitz continuous

$$\mathbf{F}(\mathbf{0}) = \mathbf{0}$$

True Dynamics



Physical System

Adaptive Controller + Parameter Update Law

$$\mathbf{u} = \mathbf{k}(\mathbf{x}, \hat{\boldsymbol{\theta}})$$

$$\dot{\hat{\boldsymbol{\theta}}} = \boldsymbol{\Gamma} \boldsymbol{\tau}(\mathbf{x}, \hat{\boldsymbol{\theta}})$$

$$\hat{\boldsymbol{\theta}} \in \mathbb{R}^p \quad \boldsymbol{\Gamma} \in \mathbb{R}^{p \times p}$$

$$\mathbf{k} : \mathbb{R}^n \times \mathbb{R}^p \rightarrow \mathbb{R}^m$$

$$\boldsymbol{\tau} : \mathbb{R}^n \times \mathbb{R}^p \rightarrow \mathbb{R}^p$$

Adaptive Controller + Parameter Update Law

$$\mathbf{u} = \mathbf{k}(\mathbf{x}, \hat{\boldsymbol{\theta}})$$

$$\dot{\hat{\boldsymbol{\theta}}} = \boldsymbol{\Gamma} \boldsymbol{\tau}(\mathbf{x}, \hat{\boldsymbol{\theta}})$$

$$\hat{\boldsymbol{\theta}} \in \mathbb{R}^p \quad \boldsymbol{\Gamma} \in \mathbb{R}^{p \times p}$$

$$\mathbf{k} : \mathbb{R}^n \times \mathbb{R}^p \rightarrow \mathbb{R}^m$$

$$\boldsymbol{\tau} : \mathbb{R}^n \times \mathbb{R}^p \rightarrow \mathbb{R}^p$$

Assumptions

(A1) \mathbf{k} locally Lipschitz continuous on $(\mathbb{R}^n \setminus \{\mathbf{0}\}) \times \mathbb{R}^p$

(A2) $\mathbf{k}(\mathbf{0}, \hat{\boldsymbol{\theta}}) = \mathbf{0} \quad \forall \hat{\boldsymbol{\theta}} \in \mathbb{R}^p$

(A3) $\boldsymbol{\tau}$ locally Lipschitz continuous on $\mathbb{R}^n \times \mathbb{R}^p$

(A4) $\boldsymbol{\Gamma} \in \mathbb{R}^{p \times p}$ is symmetric and positive-definite

Adaptive Controller + Parameter Update Law

$$\mathbf{u} = \mathbf{k}(\mathbf{x}, \hat{\boldsymbol{\theta}})$$

$$\dot{\hat{\boldsymbol{\theta}}} = \boldsymbol{\Gamma} \boldsymbol{\tau}(\mathbf{x}, \hat{\boldsymbol{\theta}})$$

$$\hat{\boldsymbol{\theta}} \in \mathbb{R}^p \quad \boldsymbol{\Gamma} \in \mathbb{R}^{p \times p}$$

$$\mathbf{k} : \mathbb{R}^n \times \mathbb{R}^p \rightarrow \mathbb{R}^m$$

$$\boldsymbol{\tau} : \mathbb{R}^n \times \mathbb{R}^p \rightarrow \mathbb{R}^p$$

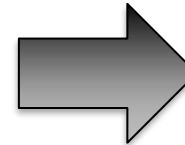
Assumptions

(A1) \mathbf{k} locally Lipschitz continuous on $(\mathbb{R}^n \setminus \{\mathbf{0}\}) \times \mathbb{R}^p$

(A2) $\mathbf{k}(\mathbf{0}, \hat{\boldsymbol{\theta}}) = \mathbf{0} \quad \forall \hat{\boldsymbol{\theta}} \in \mathbb{R}^p$

(A3) $\boldsymbol{\tau}$ locally Lipschitz continuous on $\mathbb{R}^n \times \mathbb{R}^p$

(A4) $\boldsymbol{\Gamma} \in \mathbb{R}^{p \times p}$ is symmetric and positive-definite



Composite Dynamics

$$\begin{bmatrix} \dot{\mathbf{x}} \\ \dot{\hat{\boldsymbol{\theta}}} \end{bmatrix} = \begin{bmatrix} \mathbf{f}(\mathbf{x}) + \mathbf{F}(\mathbf{x})\boldsymbol{\theta}^* + \mathbf{g}(\mathbf{x})\mathbf{k}(\mathbf{x}, \hat{\boldsymbol{\theta}}) \\ \boldsymbol{\Gamma} \boldsymbol{\tau}(\mathbf{x}, \hat{\boldsymbol{\theta}}) \end{bmatrix}$$

Global Adaptive Stabilizability

$$\begin{aligned} \mathbf{u} &= \mathbf{k}(\mathbf{x}, \hat{\boldsymbol{\theta}}) \\ \dot{\hat{\boldsymbol{\theta}}} &= \Gamma \boldsymbol{\tau}(\mathbf{x}, \hat{\boldsymbol{\theta}}) \end{aligned} \quad +(\text{A1})-(\text{A4})$$

Global Adaptive Stabilizability

$$\begin{array}{l} \mathbf{u} = \mathbf{k}(\mathbf{x}, \hat{\boldsymbol{\theta}}) \\ \dot{\hat{\boldsymbol{\theta}}} = \Gamma \boldsymbol{\tau}(\mathbf{x}, \hat{\boldsymbol{\theta}}) \end{array} \quad \begin{array}{l} +(\text{A1})-(\text{A4}) \\ \longrightarrow \end{array} \quad \begin{array}{l} (\mathbf{x}(t), \hat{\boldsymbol{\theta}}(t)) \text{ globally bounded} \\ \lim_{t \rightarrow \infty} \mathbf{x}(t) = \mathbf{0} \end{array}$$

Global Adaptive Stabilizability

$$\begin{aligned} \mathbf{u} &= \mathbf{k}(\mathbf{x}, \hat{\boldsymbol{\theta}}) \\ \dot{\hat{\boldsymbol{\theta}}} &= \boldsymbol{\Gamma} \boldsymbol{\tau}(\mathbf{x}, \hat{\boldsymbol{\theta}}) \end{aligned} \quad +(\text{A1})-(\text{A4}) \quad \longrightarrow \quad \begin{aligned} &(\mathbf{x}(t), \hat{\boldsymbol{\theta}}(t)) \text{ globally bounded} \\ &\lim_{t \rightarrow \infty} \mathbf{x}(t) = \mathbf{0} \end{aligned}$$

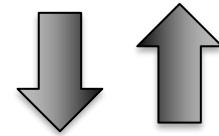
Adaptive Control Lyapunov Functions (aCLFs)^[13]

$$\begin{aligned} \alpha_1(\|\mathbf{x}\|, \boldsymbol{\theta}) &\leq V_a(\mathbf{x}, \boldsymbol{\theta}) \leq \alpha_2(\|\mathbf{x}\|, \boldsymbol{\theta}) \\ \inf_{\mathbf{u} \in \mathbb{R}^m} \frac{\partial V_a}{\partial \mathbf{x}}(\mathbf{x}, \boldsymbol{\theta}) \left(\mathbf{f}(\mathbf{x}) + \mathbf{F}(\mathbf{x}) \left(\boldsymbol{\theta} + \boldsymbol{\Gamma} \frac{\partial V_a}{\partial \boldsymbol{\theta}}(\mathbf{x}, \boldsymbol{\theta}) \right) + \mathbf{g}(\mathbf{x}) \mathbf{u} \right) &\leq -\alpha_3(\|\mathbf{x}\|, \boldsymbol{\theta}) \\ \alpha_i(\cdot, \boldsymbol{\theta}) &\in \mathcal{K}_\infty \quad \forall \boldsymbol{\theta} \in \mathbb{R}^p \end{aligned}$$

[13] M. Krstic, P.V. Kokotovic, Control Lyapunov functions for adaptive nonlinear stabilization, 1995.

Global Adaptive Stabilizability

$$\begin{array}{l}
 \mathbf{u} = \mathbf{k}(\mathbf{x}, \hat{\boldsymbol{\theta}}) \\
 \dot{\hat{\boldsymbol{\theta}}} = \boldsymbol{\Gamma} \boldsymbol{\tau}(\mathbf{x}, \hat{\boldsymbol{\theta}})
 \end{array}
 \begin{array}{l}
 +(\text{A1})-(\text{A4}) \\
 \longrightarrow
 \end{array}
 \begin{array}{l}
 (\mathbf{x}(t), \hat{\boldsymbol{\theta}}(t)) \text{ globally bounded} \\
 \lim_{t \rightarrow \infty} \mathbf{x}(t) = \mathbf{0}
 \end{array}$$



Adaptive Control Lyapunov Functions (aCLFs)^[13]

$$\begin{array}{l}
 \alpha_1(\|\mathbf{x}\|, \boldsymbol{\theta}) \leq V_a(\mathbf{x}, \boldsymbol{\theta}) \leq \alpha_2(\|\mathbf{x}\|, \boldsymbol{\theta}) \\
 \inf_{\mathbf{u} \in \mathbb{R}^m} \frac{\partial V_a}{\partial \mathbf{x}}(\mathbf{x}, \boldsymbol{\theta}) \left(\mathbf{f}(\mathbf{x}) + \mathbf{F}(\mathbf{x}) \left(\boldsymbol{\theta} + \boldsymbol{\Gamma} \frac{\partial V_a}{\partial \boldsymbol{\theta}}(\mathbf{x}, \boldsymbol{\theta}) \right) + \mathbf{g}(\mathbf{x}) \mathbf{u} \right) \leq -\alpha_3(\|\mathbf{x}\|, \boldsymbol{\theta}) \\
 \alpha_i(\cdot, \boldsymbol{\theta}) \in \mathcal{K}_\infty \quad \forall \boldsymbol{\theta} \in \mathbb{R}^p
 \end{array}$$

[13] M. Krstic, P.V. Kokotovic, Control Lyapunov functions for adaptive nonlinear stabilization, 1995.

Global Adaptive Stabilizability

$$\begin{aligned} \mathbf{u} &= \mathbf{k}(\mathbf{x}, \hat{\boldsymbol{\theta}}) \\ \dot{\hat{\boldsymbol{\theta}}} &= \boldsymbol{\Gamma} \boldsymbol{\tau}(\mathbf{x}, \hat{\boldsymbol{\theta}}) \end{aligned} \quad +(\text{A1})-(\text{A4}) \quad \longrightarrow \quad \begin{aligned} &(\mathbf{x}(t), \hat{\boldsymbol{\theta}}(t)) \text{ globally bounded} \\ &\lim_{t \rightarrow \infty} \mathbf{x}(t) = \mathbf{0} \end{aligned}$$



Adaptive Control Lyapunov Functions (aCLFs)^[13]

$$\begin{aligned} \alpha_1(\|\mathbf{x}\|, \boldsymbol{\theta}) &\leq V_a(\mathbf{x}, \boldsymbol{\theta}) \leq \alpha_2(\|\mathbf{x}\|, \boldsymbol{\theta}) \\ \inf_{\mathbf{u} \in \mathbb{R}^m} \frac{\partial V_a}{\partial \mathbf{x}}(\mathbf{x}, \boldsymbol{\theta}) \left(\mathbf{f}(\mathbf{x}) + \mathbf{F}(\mathbf{x}) \left(\boldsymbol{\theta} + \boldsymbol{\Gamma} \frac{\partial V_a}{\partial \boldsymbol{\theta}}(\mathbf{x}, \boldsymbol{\theta}) \right) + \mathbf{g}(\mathbf{x}) \mathbf{u} \right) &\leq -\alpha_3(\|\mathbf{x}\|, \boldsymbol{\theta}) \\ \alpha_i(\cdot, \boldsymbol{\theta}) &\in \mathcal{K}_\infty \quad \forall \boldsymbol{\theta} \in \mathbb{R}^p \end{aligned}$$

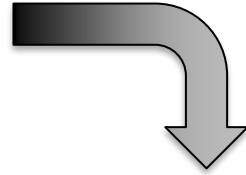
[13] M. Krstic, P.V. Kokotovic, Control Lyapunov functions for adaptive nonlinear stabilization, 1995.

Parameter Error

$$\tilde{\theta} = \theta^* - \hat{\theta}$$

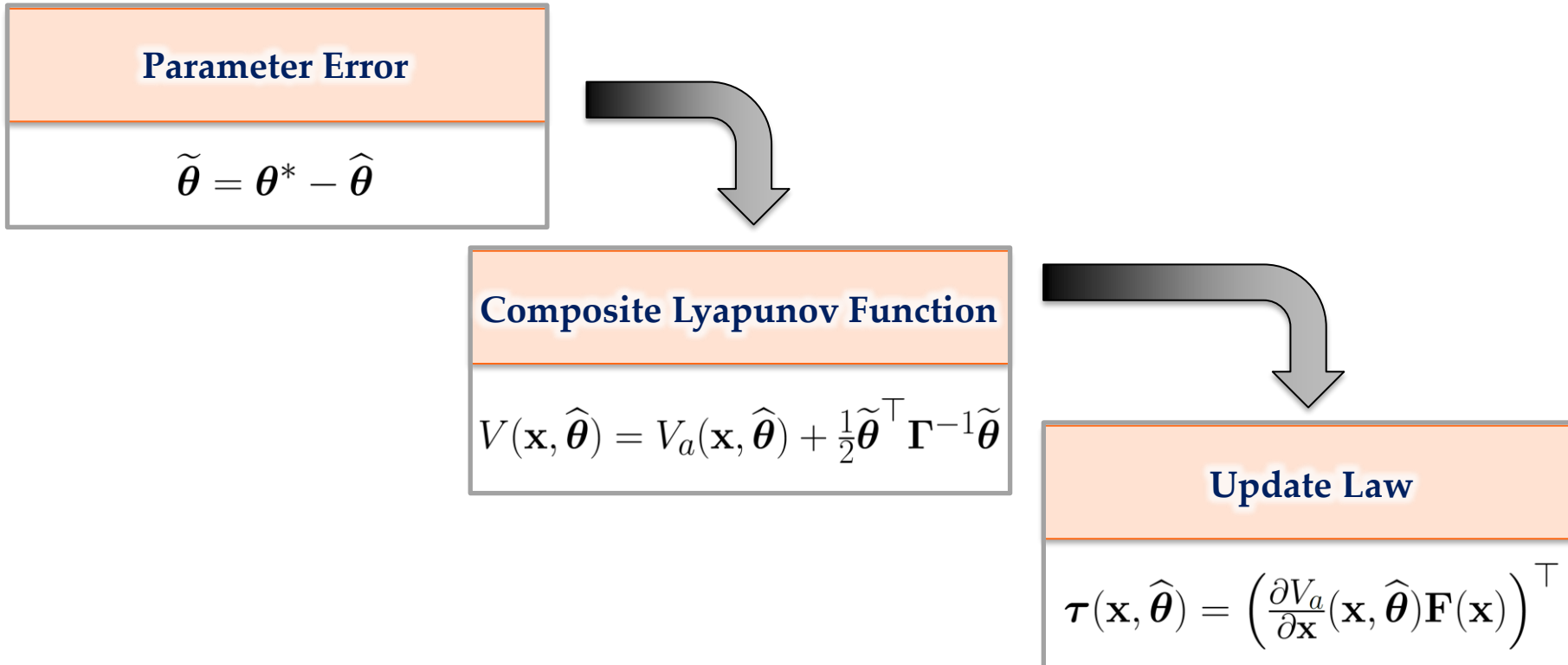
Parameter Error

$$\tilde{\theta} = \theta^* - \hat{\theta}$$

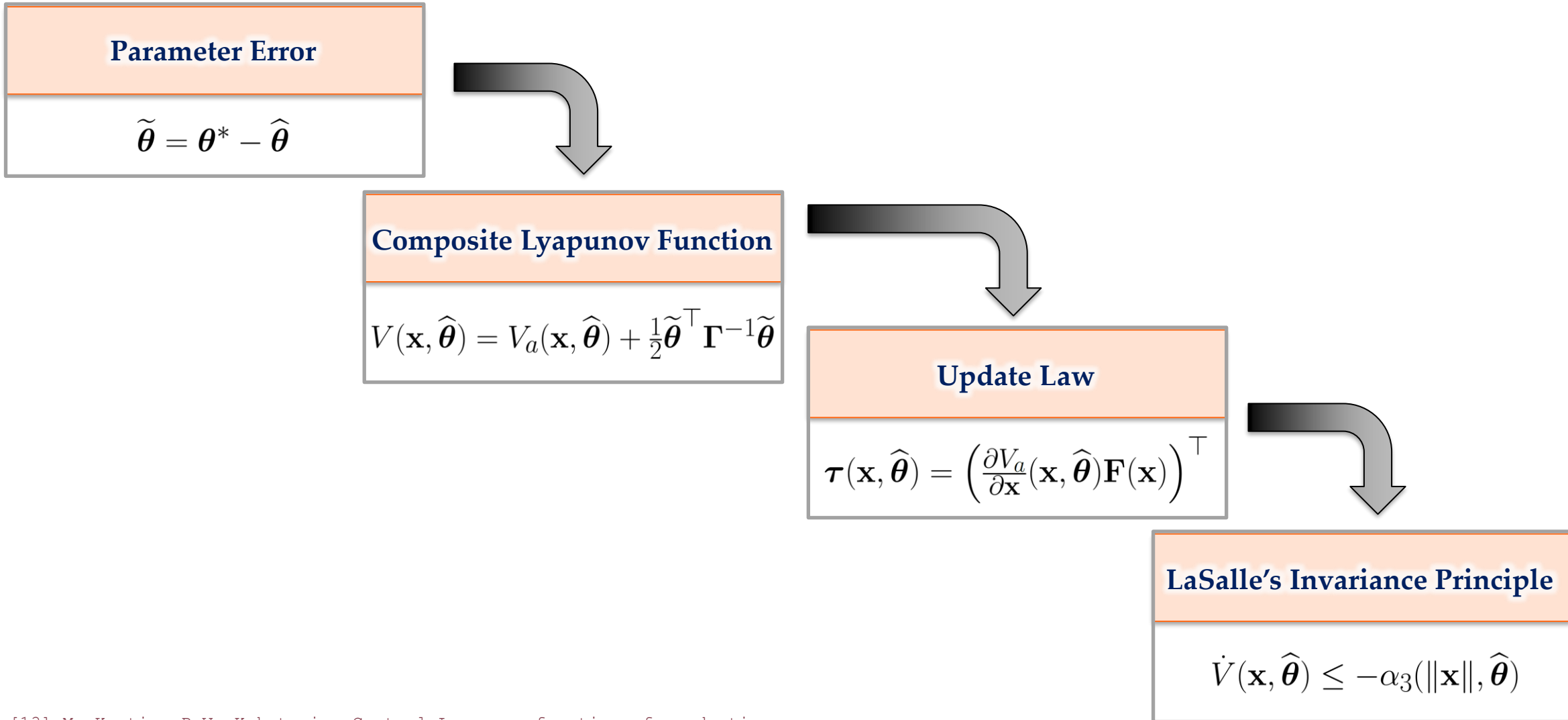


Composite Lyapunov Function

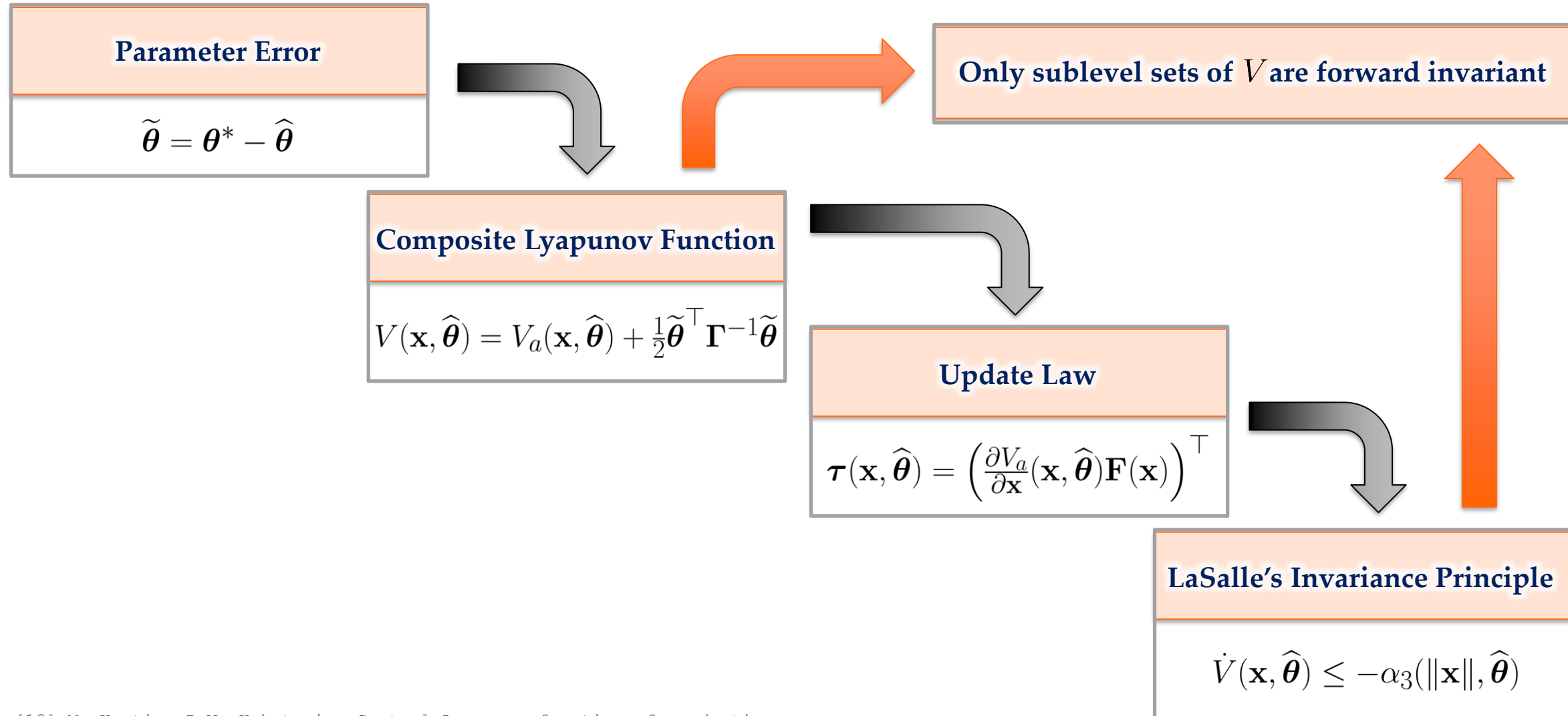
$$V(\mathbf{x}, \hat{\theta}) = V_a(\mathbf{x}, \hat{\theta}) + \frac{1}{2} \tilde{\theta}^\top \Gamma^{-1} \tilde{\theta}$$



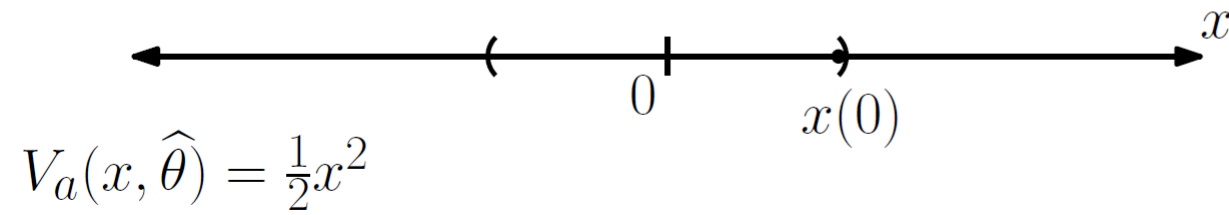
[13] M. Krstic, P.V. Kokotovic, Control Lyapunov functions for adaptive nonlinear stabilization, 1995.



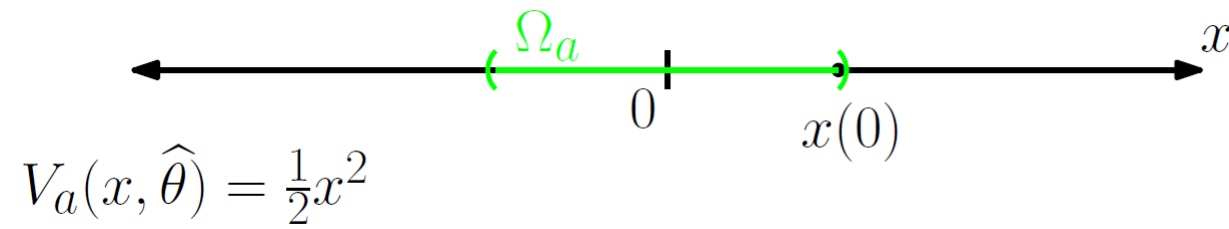
[13] M. Krstic, P.V. Kokotovic, Control Lyapunov functions for adaptive nonlinear stabilization, 1995.

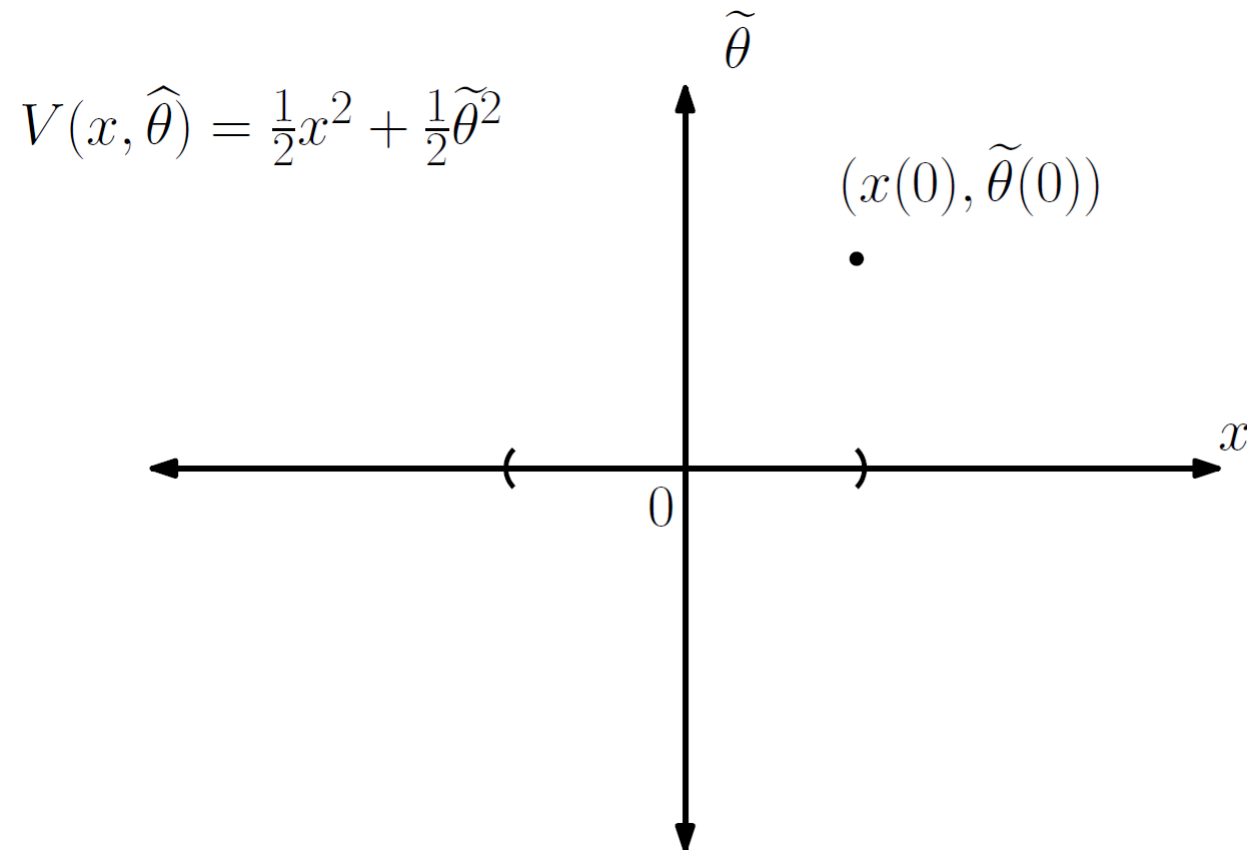


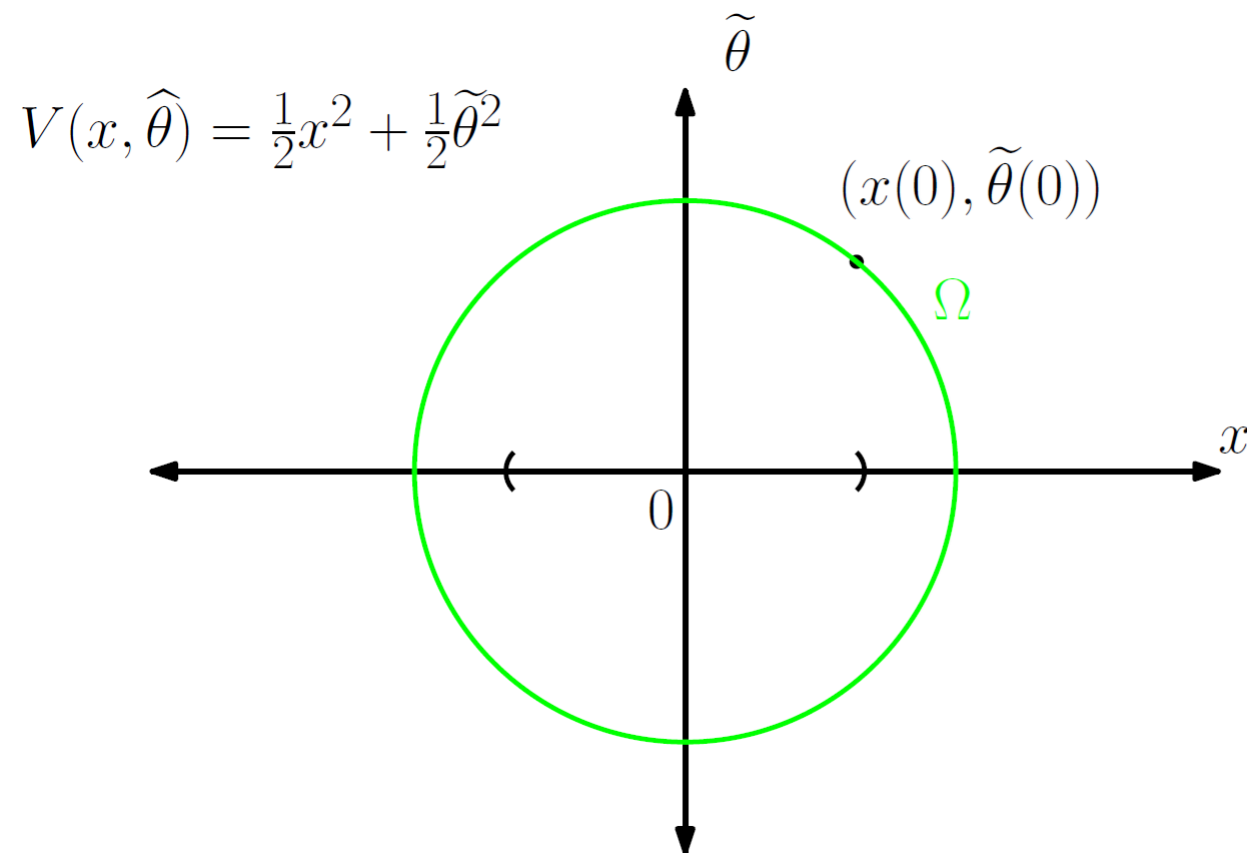
[13] M. Krstic, P.V. Kokotovic, Control Lyapunov functions for adaptive nonlinear stabilization, 1995.

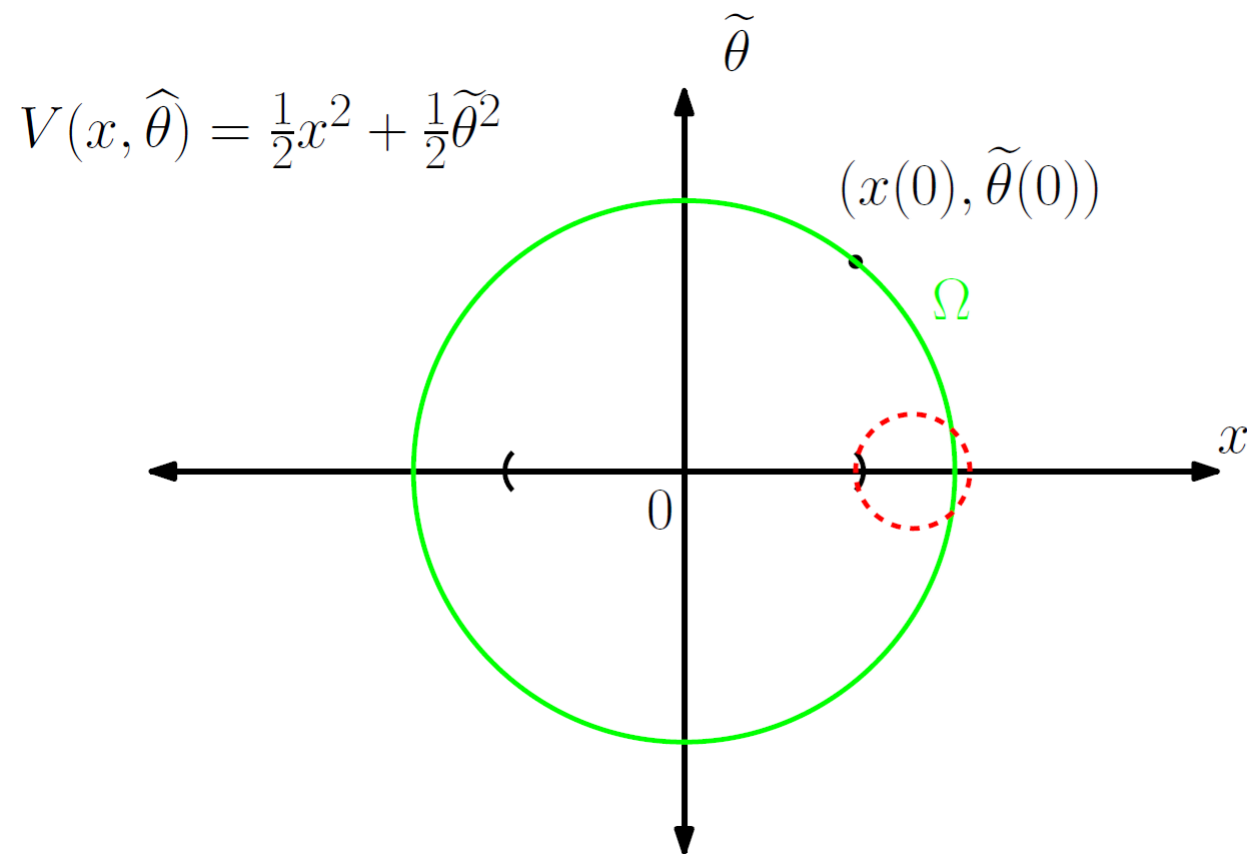


$$V_a(x, \hat{\theta}) = \frac{1}{2}x^2$$







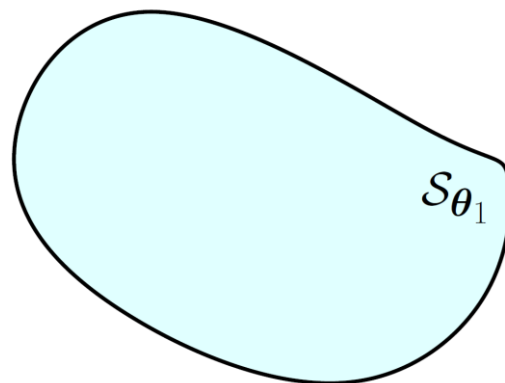


Parametric Safe Sets

$$\mathcal{S}_\theta \triangleq \{\mathbf{x} \in \mathbb{R}^n \mid h_a(\mathbf{x}, \theta) \geq 0\}$$

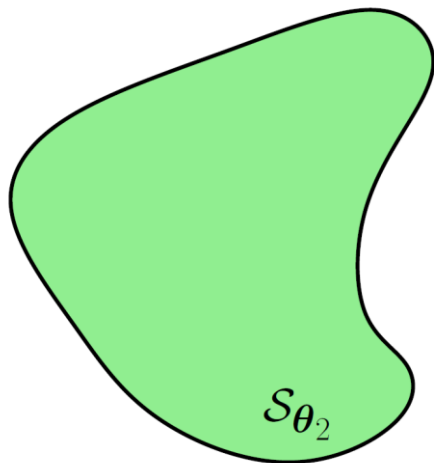
Parametric Safe Sets

$$\mathcal{S}_\theta \triangleq \{\mathbf{x} \in \mathbb{R}^n \mid h_a(\mathbf{x}, \theta) \geq 0\}$$



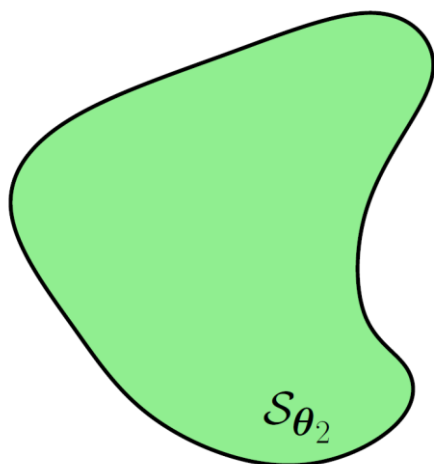
Parametric Safe Sets

$$\mathcal{S}_\theta \triangleq \{\mathbf{x} \in \mathbb{R}^n \mid h_a(\mathbf{x}, \theta) \geq 0\}$$



Parametric Safe Sets

$$\mathcal{S}_\theta \triangleq \{\mathbf{x} \in \mathbb{R}^n \mid h_a(\mathbf{x}, \theta) \geq 0\}$$

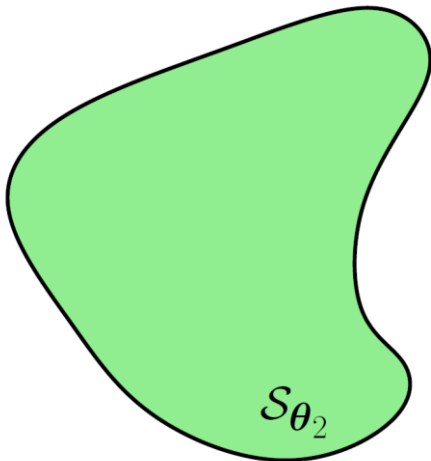


Adaptively Safe

$$\begin{aligned} \mathbf{u} &= \mathbf{k}(\mathbf{x}, \hat{\theta}) \\ \dot{\hat{\theta}} &= \Gamma \tau(\mathbf{x}, \hat{\theta}) \end{aligned} \quad +(\text{A1})-(\text{A4})$$

Parametric Safe Sets

$$\mathcal{S}_\theta \triangleq \{\mathbf{x} \in \mathbb{R}^n \mid h_a(\mathbf{x}, \theta) \geq 0\}$$

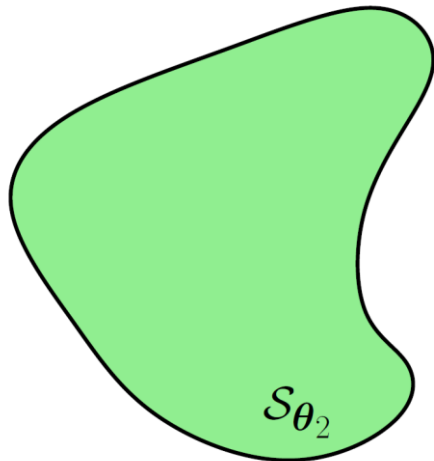


Adaptively Safe

$$\begin{aligned} \mathbf{u} &= \mathbf{k}(\mathbf{x}, \hat{\theta}) \\ \dot{\hat{\theta}} &= \Gamma \tau(\mathbf{x}, \hat{\theta}) \end{aligned} \quad \begin{array}{l} \text{+(A1)-(A4)} \\ \end{array} \quad \longrightarrow \quad \mathbf{x}(t) \in \mathcal{S}_{\hat{\theta}(t)} \quad \forall t \geq 0$$

Parametric Safe Sets

$$\mathcal{S}_\theta \triangleq \{\mathbf{x} \in \mathbb{R}^n \mid h_a(\mathbf{x}, \theta) \geq 0\}$$



Adaptively Safe

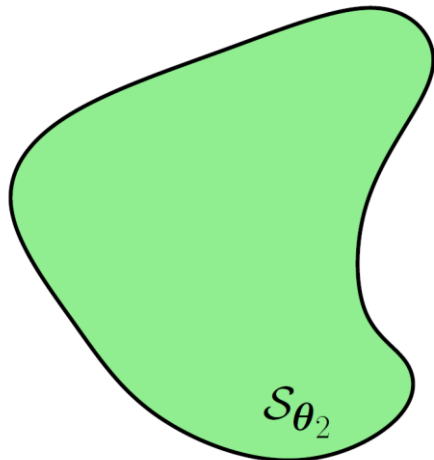
$$\begin{aligned} \mathbf{u} &= \mathbf{k}(\mathbf{x}, \hat{\theta}) \\ \dot{\hat{\theta}} &= \Gamma \tau(\mathbf{x}, \hat{\theta}) \end{aligned} \quad \text{+(A1)-(A4)} \quad \longrightarrow \quad \mathbf{x}(t) \in \mathcal{S}_{\hat{\theta}(t)} \quad \forall t \geq 0$$

Adaptive Control Barrier Functions (aCBFs)

$$\sup_{\mathbf{u} \in \mathbb{R}^m} \frac{\partial h_a}{\partial \mathbf{x}}(\mathbf{x}, \theta) \left(\mathbf{f}(\mathbf{x}) + \mathbf{F}(\mathbf{x}) \left(\theta - \Gamma \frac{\partial h_a}{\partial \theta}(\mathbf{x}, \theta) \right) + \mathbf{g}(\mathbf{x}) \mathbf{u} \right) \geq 0$$

Parametric Safe Sets

$$\mathcal{S}_\theta \triangleq \{\mathbf{x} \in \mathbb{R}^n \mid h_a(\mathbf{x}, \theta) \geq 0\}$$



Adaptively Safe

$$\begin{aligned} \mathbf{u} &= \mathbf{k}(\mathbf{x}, \hat{\theta}) \\ \dot{\hat{\theta}} &= \Gamma \tau(\mathbf{x}, \hat{\theta}) \end{aligned} \quad \text{+(A1)-(A4)} \quad \Rightarrow \quad \mathbf{x}(t) \in \mathcal{S}_{\hat{\theta}(t)} \quad \forall t \geq 0$$

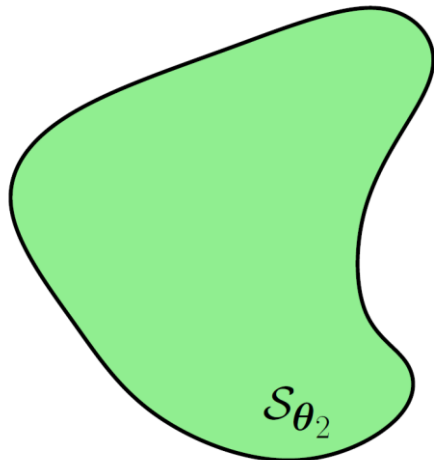


Adaptive Control Barrier Functions (aCBFs)

$$\sup_{\mathbf{u} \in \mathbb{R}^m} \frac{\partial h_a}{\partial \mathbf{x}}(\mathbf{x}, \theta) \left(\mathbf{f}(\mathbf{x}) + \mathbf{F}(\mathbf{x}) \left(\theta - \Gamma \frac{\partial h_a}{\partial \theta}(\mathbf{x}, \theta) \right) + \mathbf{g}(\mathbf{x}) \mathbf{u} \right) \geq 0$$

Parametric Safe Sets

$$\mathcal{S}_\theta \triangleq \{\mathbf{x} \in \mathbb{R}^n \mid h_a(\mathbf{x}, \theta) \geq 0\}$$



Adaptively Safe

$$\begin{aligned} \mathbf{u} &= \mathbf{k}(\mathbf{x}, \hat{\theta}) \\ \dot{\hat{\theta}} &= \Gamma \tau(\mathbf{x}, \hat{\theta}) \end{aligned} \quad \text{+(A1)-(A4)} \quad \longrightarrow \quad \mathbf{x}(t) \in \mathcal{S}_{\hat{\theta}(t)} \quad \forall t \geq 0$$



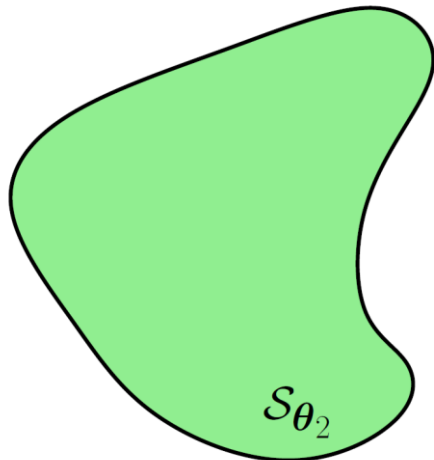
Adaptive Control Barrier Functions (aCBFs)

$$\sup_{\mathbf{u} \in \mathbb{R}^m} \frac{\partial h_a}{\partial \mathbf{x}}(\mathbf{x}, \theta) \left(\mathbf{f}(\mathbf{x}) + \mathbf{F}(\mathbf{x}) \left(\theta - \Gamma \frac{\partial h_a}{\partial \theta}(\mathbf{x}, \theta) \right) + \mathbf{g}(\mathbf{x}) \mathbf{u} \right) \geq 0$$

$$\mathbf{x}_0 \in \text{int}(\mathcal{S}_{\hat{\theta}_0})$$

Parametric Safe Sets

$$\mathcal{S}_\theta \triangleq \{\mathbf{x} \in \mathbb{R}^n \mid h_a(\mathbf{x}, \theta) \geq 0\}$$



Adaptively Safe

$$\begin{aligned} \mathbf{u} &= \mathbf{k}(\mathbf{x}, \hat{\theta}) \\ \dot{\hat{\theta}} &= \Gamma \tau(\mathbf{x}, \hat{\theta}) \end{aligned} \quad +(\text{A1})\text{-(A4)} \quad \longrightarrow \quad \mathbf{x}(t) \in \mathcal{S}_{\hat{\theta}(t)} \quad \forall t \geq 0$$



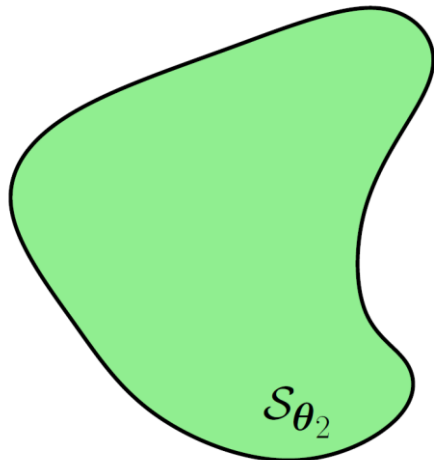
Adaptive Control Barrier Functions (aCBFs)

$$\sup_{\mathbf{u} \in \mathbb{R}^m} \frac{\partial h_a}{\partial \mathbf{x}}(\mathbf{x}, \theta) \left(\mathbf{f}(\mathbf{x}) + \mathbf{F}(\mathbf{x}) \left(\theta - \Gamma \frac{\partial h_a}{\partial \theta}(\mathbf{x}, \theta) \right) + \mathbf{g}(\mathbf{x}) \mathbf{u} \right) \geq 0$$

$$\mathbf{x}_0 \in \text{int}(\mathcal{S}_{\hat{\theta}_0}) \quad \|\tilde{\theta}_0\|_2 \leq c$$

Parametric Safe Sets

$$\mathcal{S}_\theta \triangleq \{\mathbf{x} \in \mathbb{R}^n \mid h_a(\mathbf{x}, \theta) \geq 0\}$$



Adaptively Safe

$$\begin{aligned} \mathbf{u} &= \mathbf{k}(\mathbf{x}, \hat{\theta}) \\ \dot{\hat{\theta}} &= \Gamma \tau(\mathbf{x}, \hat{\theta}) \end{aligned} \quad +(\text{A1})-(\text{A4}) \quad \longrightarrow \quad \mathbf{x}(t) \in \mathcal{S}_{\hat{\theta}(t)} \quad \forall t \geq 0$$



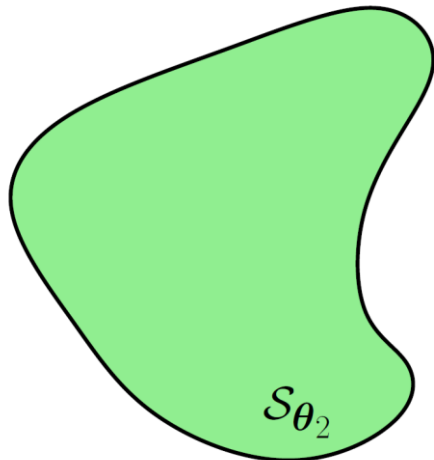
Adaptive Control Barrier Functions (aCBFs)

$$\sup_{\mathbf{u} \in \mathbb{R}^m} \frac{\partial h_a}{\partial \mathbf{x}}(\mathbf{x}, \theta) \left(\mathbf{f}(\mathbf{x}) + \mathbf{F}(\mathbf{x}) \left(\theta - \Gamma \frac{\partial h_a}{\partial \theta}(\mathbf{x}, \theta) \right) + \mathbf{g}(\mathbf{x}) \mathbf{u} \right) \geq 0$$

$$\mathbf{x}_0 \in \text{int}(\mathcal{S}_{\hat{\theta}_0}) \quad \|\tilde{\theta}_0\|_2 \leq c \quad \lambda_{\min}(\Gamma) \geq \frac{c^2}{2h_a(\mathbf{x}_0, \hat{\theta}_0)}$$

Parametric Safe Sets

$$\mathcal{S}_\theta \triangleq \{\mathbf{x} \in \mathbb{R}^n \mid h_a(\mathbf{x}, \theta) \geq 0\}$$



Adaptively Safe

$$\begin{aligned} \mathbf{u} &= \mathbf{k}(\mathbf{x}, \hat{\theta}) \\ \dot{\hat{\theta}} &= \Gamma \tau(\mathbf{x}, \hat{\theta}) \end{aligned} \quad \text{+(A1)-(A4)} \quad \longrightarrow \quad \mathbf{x}(t) \in \mathcal{S}_{\hat{\theta}(t)} \quad \forall t \geq 0$$



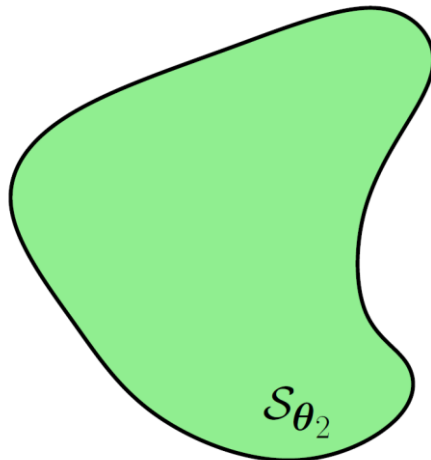
Adaptive Control Barrier Functions (aCBFs)

$$\sup_{\mathbf{u} \in \mathbb{R}^m} \frac{\partial h_a}{\partial \mathbf{x}}(\mathbf{x}, \theta) \left(\mathbf{f}(\mathbf{x}) + \mathbf{F}(\mathbf{x}) \left(\theta - \Gamma \frac{\partial h_a}{\partial \theta}(\mathbf{x}, \theta) \right) + \mathbf{g}(\mathbf{x}) \mathbf{u} \right) \geq 0$$

$$\mathbf{x}_0 \in \text{int}(\mathcal{S}_{\hat{\theta}_0}) \quad \|\tilde{\theta}_0\|_2 \leq c \quad \lambda_{\min}(\Gamma) \geq \frac{c^2}{2h_a(\mathbf{x}_0, \hat{\theta}_0)}$$

Parametric Safe Sets

$$\mathcal{S}_\theta \triangleq \{\mathbf{x} \in \mathbb{R}^n \mid h_a(\mathbf{x}, \theta) \geq 0\}$$



Adaptively Safe

$$\begin{aligned} \mathbf{u} &= \mathbf{k}(\mathbf{x}, \hat{\theta}) \\ \dot{\hat{\theta}} &= \Gamma \tau(\mathbf{x}, \hat{\theta}) \end{aligned} \quad +(\text{A1})\text{-(A4)} \quad \longrightarrow \quad \mathbf{x}(t) \in \mathcal{S}_{\hat{\theta}(t)} \quad \forall t \geq 0$$



Adaptive Control Barrier Functions (aCBFs)

$$\sup_{\mathbf{u} \in \mathbb{R}^m} \frac{\partial h_a}{\partial \mathbf{x}}(\mathbf{x}, \theta) \left(\mathbf{f}(\mathbf{x}) + \mathbf{F}(\mathbf{x}) \left(\theta - \Gamma \frac{\partial h_a}{\partial \theta}(\mathbf{x}, \theta) \right) + \mathbf{g}(\mathbf{x}) \mathbf{u} \right) \geq 0$$

$$\mathbf{x}_0 \in \text{int}(\mathcal{S}_{\hat{\theta}_0}) \quad \|\tilde{\theta}_0\|_2 \leq c \quad \lambda_{\min}(\Gamma) \geq \frac{c^2}{2h_a(\mathbf{x}_0, \hat{\theta}_0)}$$

[14] S. Prajna, Optimization-based methods for nonlinear and hybrid systems verification, 2005.

[15] P. Wieland and F. Allgöwer, Constructive safety using control barrier functions, 2007.

Composite Barrier Function

$$h(\mathbf{x}, \hat{\boldsymbol{\theta}}) = h_a(\mathbf{x}, \hat{\boldsymbol{\theta}}) - \frac{1}{2} \tilde{\boldsymbol{\theta}}^\top \boldsymbol{\Gamma}^{-1} \tilde{\boldsymbol{\theta}}$$

Composite Barrier Function

$$h(\mathbf{x}, \hat{\boldsymbol{\theta}}) = h_a(\mathbf{x}, \hat{\boldsymbol{\theta}}) - \frac{1}{2} \tilde{\boldsymbol{\theta}}^\top \boldsymbol{\Gamma}^{-1} \tilde{\boldsymbol{\theta}}$$



Assumptions

$$\mathbf{x}_0 \in \text{int}(\mathcal{S}_{\hat{\boldsymbol{\theta}}_0})$$

$$\|\tilde{\boldsymbol{\theta}}_0\|_2 \leq c$$

$$\lambda_{\min}(\boldsymbol{\Gamma}) \geq \frac{c^2}{2h_a(\mathbf{x}_0, \hat{\boldsymbol{\theta}}_0)}$$

Composite Barrier Function

$$h(\mathbf{x}, \hat{\boldsymbol{\theta}}) = h_a(\mathbf{x}, \hat{\boldsymbol{\theta}}) - \frac{1}{2} \tilde{\boldsymbol{\theta}}^\top \boldsymbol{\Gamma}^{-1} \tilde{\boldsymbol{\theta}}$$



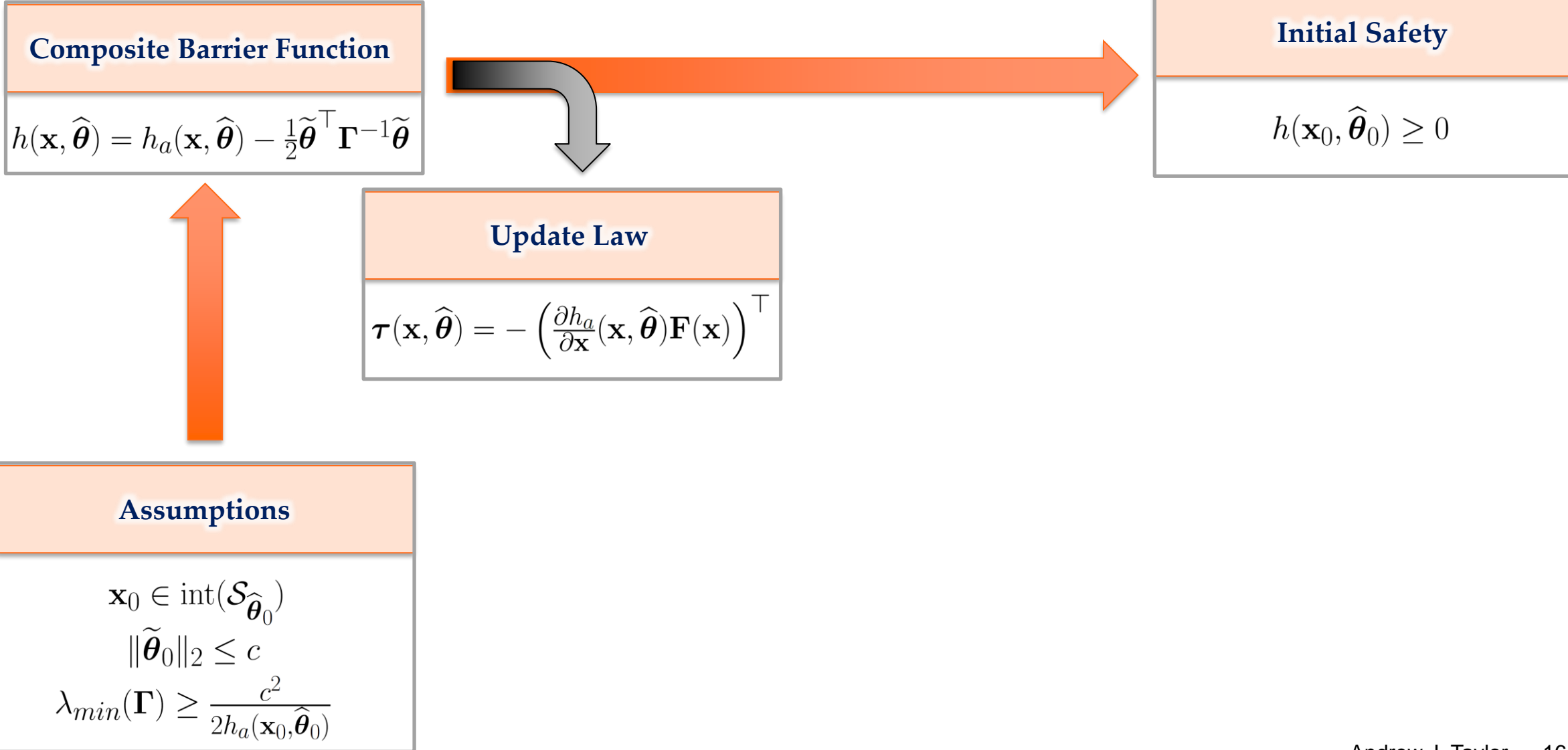
Initial Safety

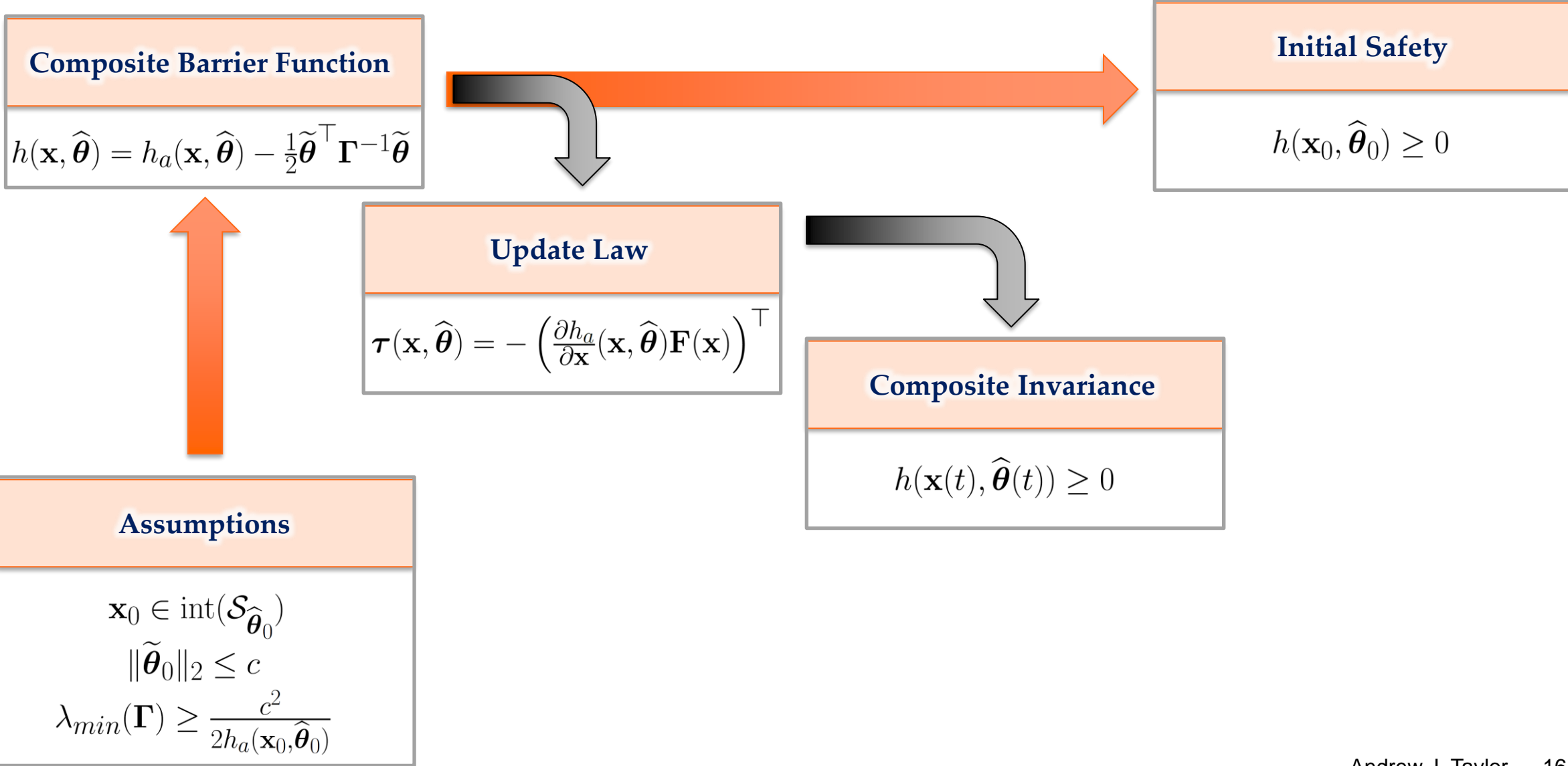
$$h(\mathbf{x}_0, \hat{\boldsymbol{\theta}}_0) \geq 0$$

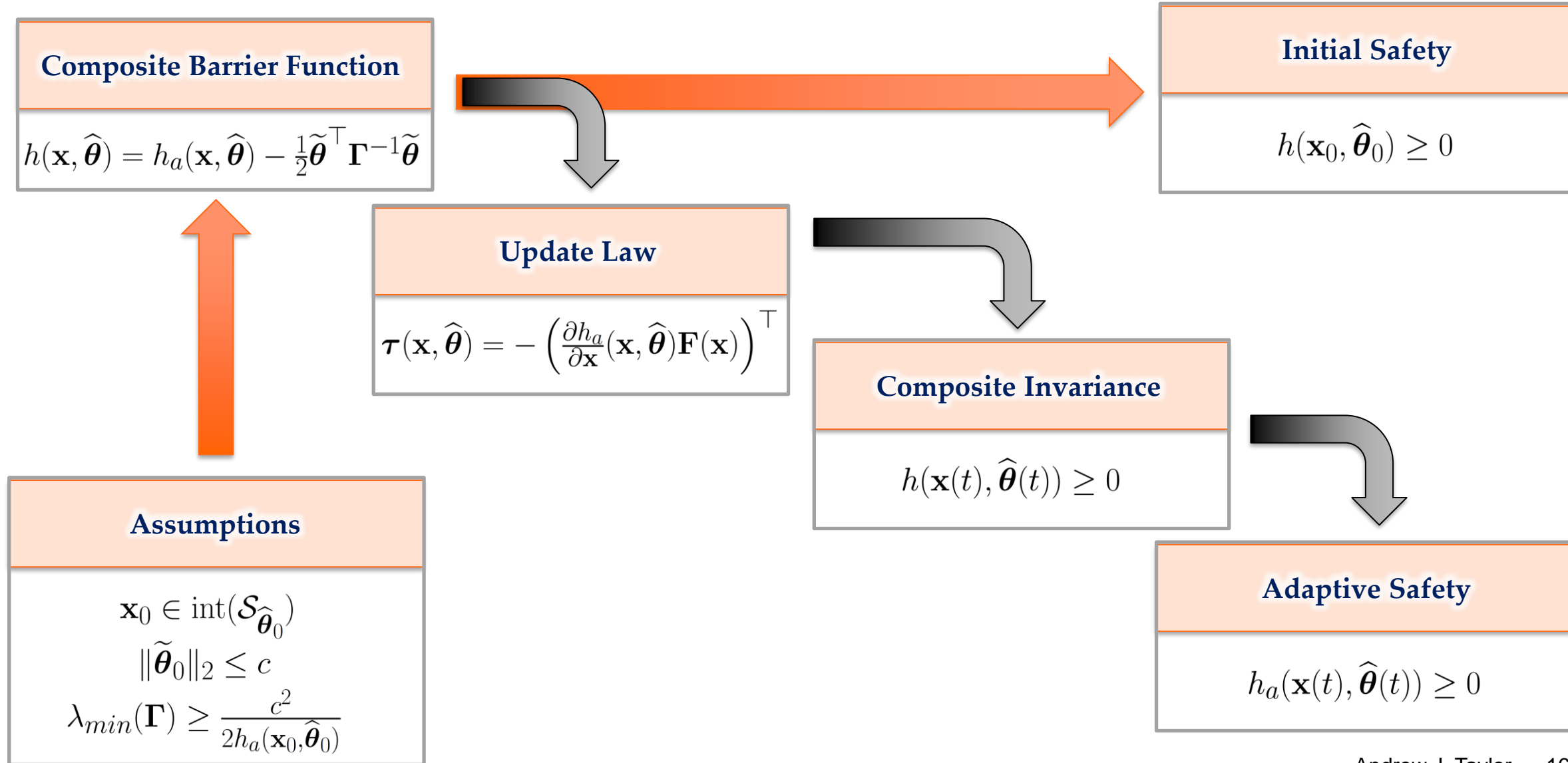
Assumptions

$$\mathbf{x}_0 \in \text{int}(\mathcal{S}_{\hat{\boldsymbol{\theta}}_0})$$
$$\|\tilde{\boldsymbol{\theta}}_0\|_2 \leq c$$
$$\lambda_{\min}(\boldsymbol{\Gamma}) \geq \frac{c^2}{2h_a(\mathbf{x}_0, \hat{\boldsymbol{\theta}}_0)}$$









Why not $\dot{h}_a(\mathbf{x}, \hat{\boldsymbol{\theta}}, \mathbf{u}) \geq -\alpha(h_a(\mathbf{x}, \hat{\boldsymbol{\theta}}))$?

[16] M. Nagumo, Über die lage der integralkurven gewöhnlicher differentialgleichungen, 1942.

Why not $\dot{h}_a(\mathbf{x}, \hat{\boldsymbol{\theta}}, \mathbf{u}) \geq -\alpha(h_a(\mathbf{x}, \hat{\boldsymbol{\theta}}))$?

[16] M. Nagumo, Über die lage der integralkurven gewöhnlicher differentialgleichungen, 1942.

Pathological Example

$$\begin{aligned}\dot{x} &= \theta + u \\ h_a(x) &= 1 - x^2 \\ h(x, \hat{\theta}) &= h_a(x) - \frac{1}{2}\gamma^{-1}\tilde{\theta}^2\end{aligned}$$

Why not $\dot{h}_a(\mathbf{x}, \hat{\boldsymbol{\theta}}, \mathbf{u}) \geq -\alpha(h_a(\mathbf{x}, \hat{\boldsymbol{\theta}}))$?

[16] M. Nagumo, Über die lage der integralkurven gewöhnlicher differentialgleichungen, 1942.

Pathological Example

$$\dot{x} = \theta + u$$

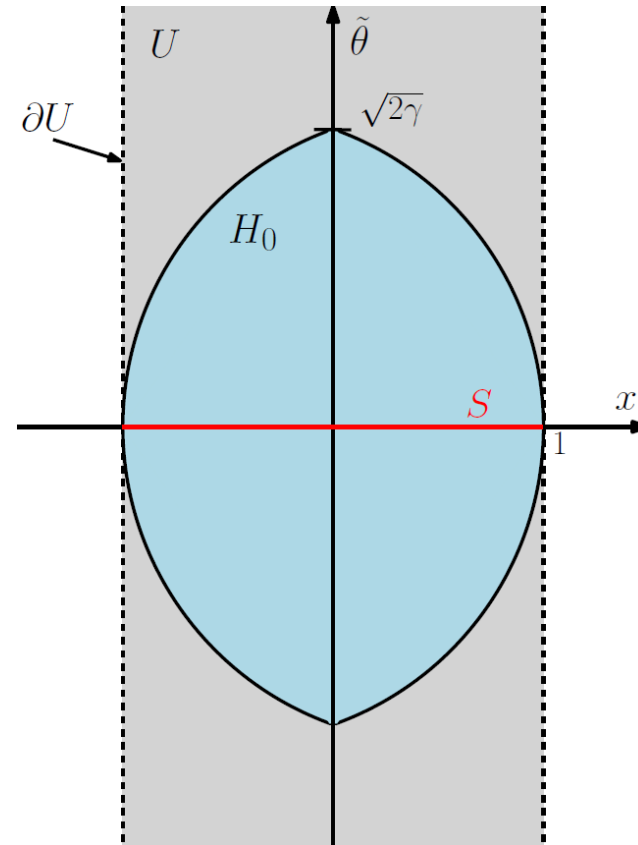
$$h_a(x) = 1 - x^2$$

$$h(x, \hat{\theta}) = h_a(x) - \frac{1}{2}\gamma^{-1}\hat{\theta}^2$$

$$\mathcal{S} \triangleq \{x \in \mathbb{R} \mid x^2 \leq 1\}$$

$$U \triangleq \{(x, \tilde{\theta}) \in \mathbb{R}^2 \mid x \in \mathcal{S}\}$$

$$H_0 \triangleq \{(x, \tilde{\theta}) \in \mathbb{R}^2 \mid h(x, \hat{\theta}) \geq 0\}$$



Liénard System

$$\begin{bmatrix} \dot{x} \\ \dot{\theta} \end{bmatrix} = \begin{bmatrix} \tilde{\theta} + \frac{1}{2}x\alpha(h_a(x)) \\ -2\gamma x \end{bmatrix}$$

Liénard System

$$\begin{bmatrix} \dot{x} \\ \dot{\tilde{\theta}} \end{bmatrix} = \begin{bmatrix} \tilde{\theta} + \frac{1}{2}x\alpha(h_a(x)) \\ -2\gamma x \end{bmatrix}$$

Liénard's Theorem^[17]

Theorem 4 (Liénard's Theorem). *Under the assumption that $F, g \in C^1(\mathbb{R})$, F and g are odd functions of x , $xg(x) > 0$ for $x \neq 0$, $F(0) = 0$, $F'(0) < 0$, F has single positive zero at $x = a$, and F increases monotonically to infinity for $x \geq a$ as $x \rightarrow \infty$, it follows that the Liénard system has exactly one limit cycle Φ and it is stable.*

Corollary 1. *The stable limit cycle Φ is symmetric about the origin and passes through a point, denoted as $P_2 = (x_2, \tilde{\theta}_2)$, such that $x_2 > a$.*

[17] L. Perko, Differential equations and dynamical systems, 2013.

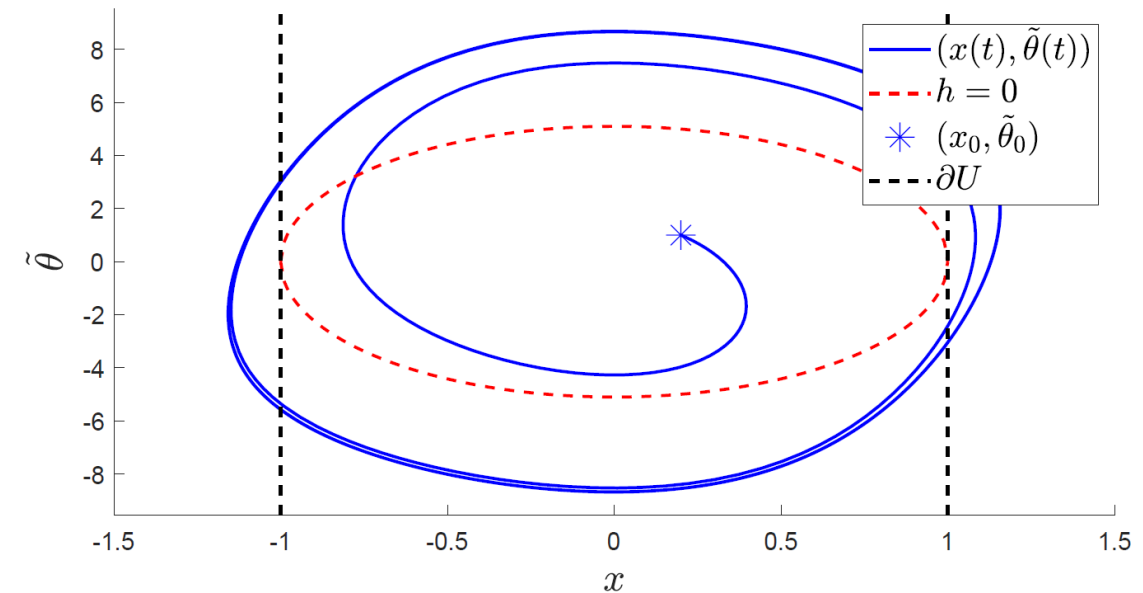
Liénard System

$$\begin{bmatrix} \dot{x} \\ \dot{\tilde{\theta}} \end{bmatrix} = \begin{bmatrix} \tilde{\theta} + \frac{1}{2}x\alpha(h_a(x)) \\ -2\gamma x \end{bmatrix}$$

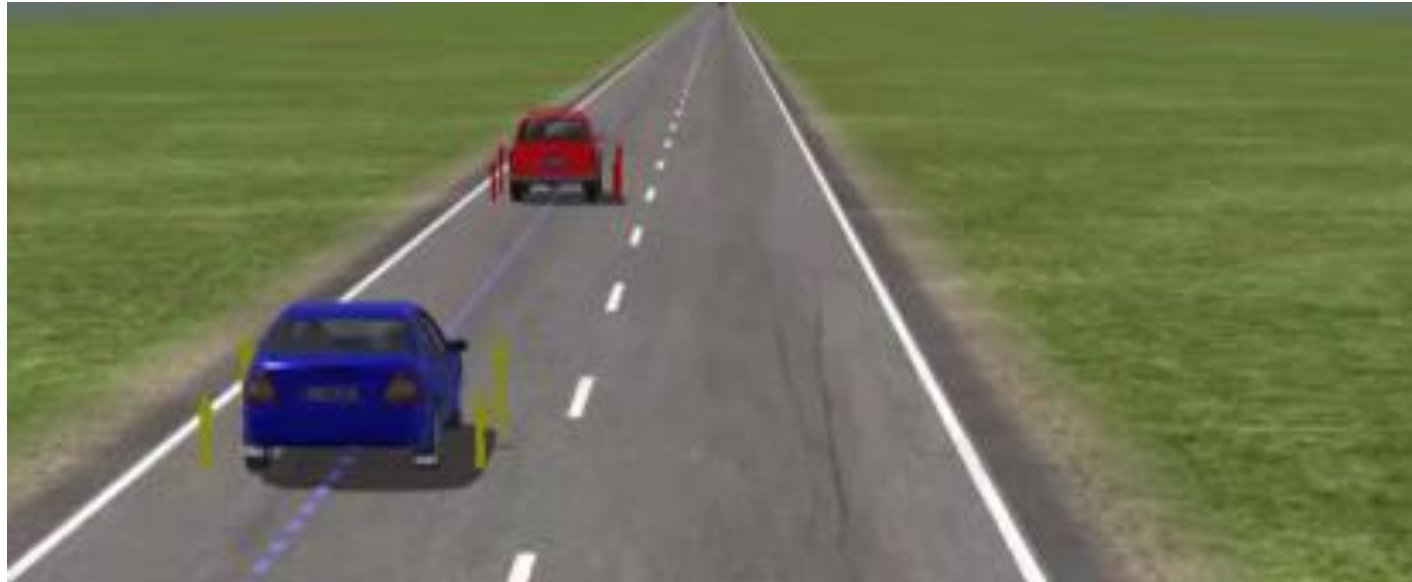
Liénard's Theorem^[17]

Theorem 4 (Liénard's Theorem). *Under the assumption that $F, g \in C^1(\mathbb{R})$, F and g are odd functions of x , $xg(x) > 0$ for $x \neq 0$, $F(0) = 0$, $F'(0) < 0$, F has single positive zero at $x = a$, and F increases monotonically to infinity for $x \geq a$ as $x \rightarrow \infty$, it follows that the Liénard system has exactly one limit cycle Φ and it is stable.*

Corollary 1. *The stable limit cycle Φ is symmetric about the origin and passes through a point, denoted as $P_2 = (x_2, \tilde{\theta}_2)$, such that $x_2 > a$.*



[17] L. Perko, Differential equations and dynamical systems, 2013.



States and Parameters

Vehicle velocity: v

Vehicle distance gap: D

Lead vehicle velocity: v_0

Vehicle mass: m

Unknown friction coefficients: f_0, f_1, f_2

Dynamics

$$\frac{d}{dt} \begin{bmatrix} v \\ D \end{bmatrix} = \begin{bmatrix} 0 \\ v_0 - v \end{bmatrix} - \frac{1}{m} \begin{bmatrix} 1 & v & v^2 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} f_0 \\ f_1 \\ f_2 \end{bmatrix} + \begin{bmatrix} \frac{1}{m} \\ 0 \end{bmatrix} u$$

States and Parameters

Vehicle velocity: v

Vehicle distance gap: D

Lead vehicle velocity: v_0

Vehicle mass: m

Unknown friction coefficients: f_0, f_1, f_2

Dynamics

$$\frac{d}{dt} \begin{bmatrix} v \\ D \end{bmatrix} = \begin{bmatrix} 0 \\ v_0 - v \end{bmatrix} - \frac{1}{m} \begin{bmatrix} 1 & v & v^2 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} f_0 \\ f_1 \\ f_2 \end{bmatrix} + \begin{bmatrix} \frac{1}{m} \\ 0 \end{bmatrix} u$$

Safety Objective

$$D \geq 1.8v$$

States and Parameters

Vehicle velocity: v
Vehicle distance gap: D
Lead vehicle velocity: v_0
Vehicle mass: m
Unknown friction coefficients: f_0, f_1, f_2

Dynamics

$$\frac{d}{dt} \begin{bmatrix} v \\ D \end{bmatrix} = \begin{bmatrix} 0 \\ v_0 - v \end{bmatrix} - \frac{1}{m} \begin{bmatrix} 1 & v & v^2 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} f_0 \\ f_1 \\ f_2 \end{bmatrix} + \begin{bmatrix} \frac{1}{m} \\ 0 \end{bmatrix} u$$

Safety Objective

$$D \geq 1.8v$$

Adaptive CBF

$$h_a(v, D) = \begin{cases} \alpha^2 & \text{if } D - 1.8v \geq \alpha \\ \alpha^2 - (D - 1.8v - \alpha)^2 & \text{if } D - 1.8v < \alpha \end{cases}$$

States and Parameters

Vehicle velocity: v
 Vehicle distance gap: D
 Lead vehicle velocity: v_0
 Vehicle mass: m
 Unknown friction coefficients: f_0, f_1, f_2

Dynamics

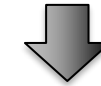
$$\frac{d}{dt} \begin{bmatrix} v \\ D \end{bmatrix} = \begin{bmatrix} 0 \\ v_0 - v \end{bmatrix} - \frac{1}{m} \begin{bmatrix} 1 & v & v^2 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} f_0 \\ f_1 \\ f_2 \end{bmatrix} + \begin{bmatrix} \frac{1}{m} \\ 0 \end{bmatrix} u$$

Safety Objective

$$D \geq 1.8v$$

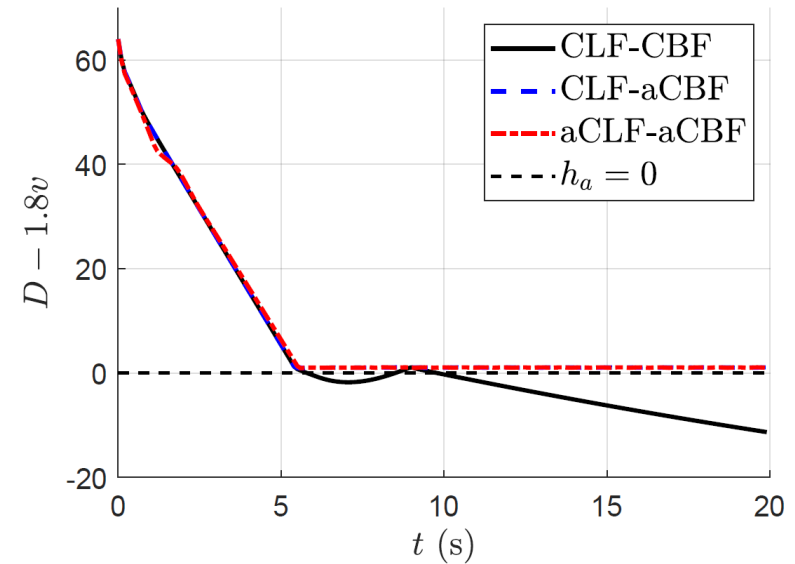
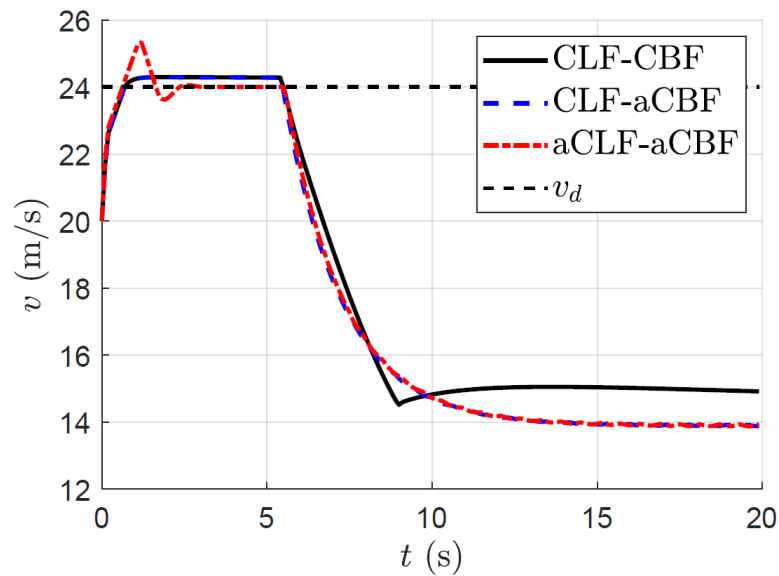
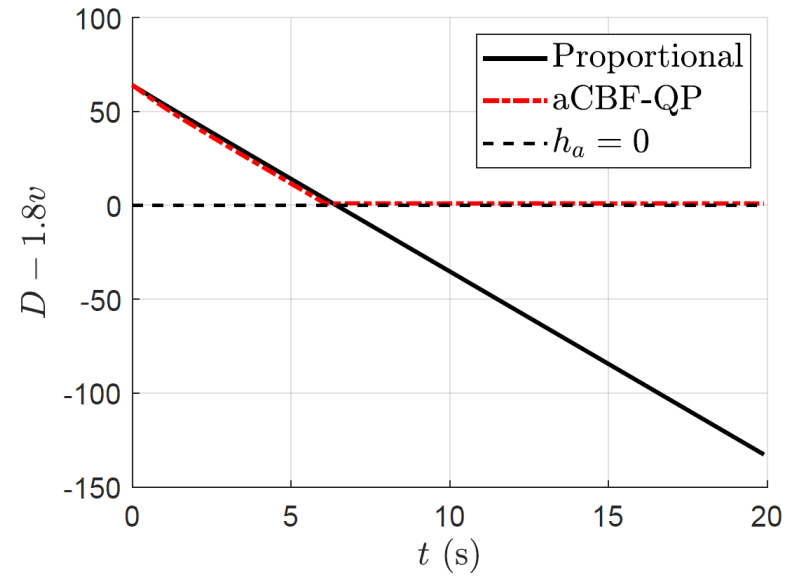
Adaptive CBF

$$h_a(v, D) = \begin{cases} \alpha^2 & \text{if } D - 1.8v \geq \alpha \\ \alpha^2 - (D - 1.8v - \alpha)^2 & \text{if } D - 1.8v < \alpha \end{cases}$$

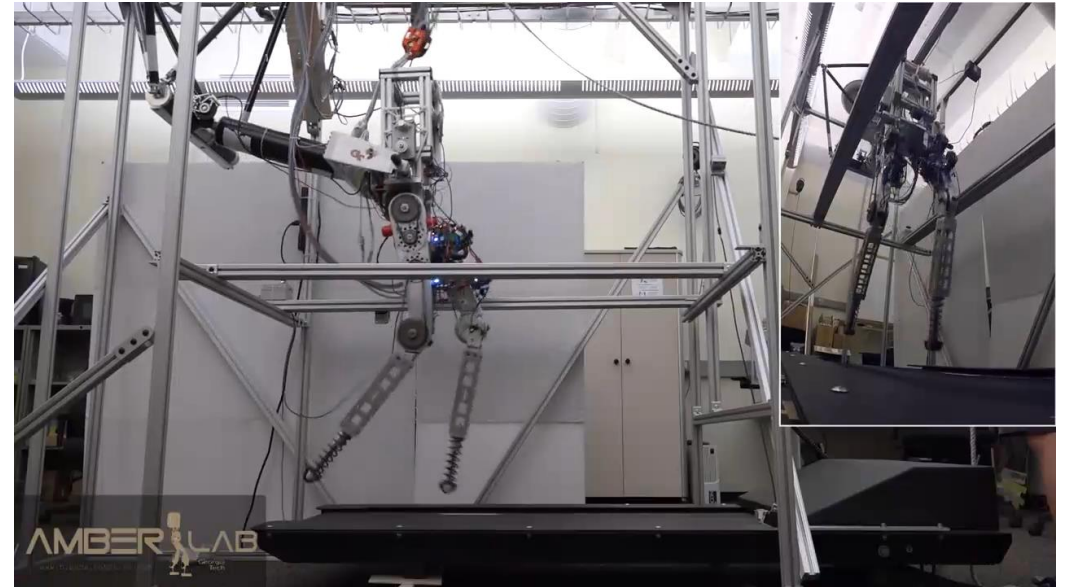


aCLF-aCBF-QP

$$\begin{aligned} \mathbf{k}(\mathbf{x}, \hat{\boldsymbol{\theta}}, \hat{\boldsymbol{\psi}}) = \operatorname{argmin} \quad & J(u) + c_V \delta_V^2 + c_p \delta_p^2 \\ \text{s.t.} \quad & \dot{V}_a(\mathbf{x}, \hat{\boldsymbol{\theta}}, \mathbf{u}) \leq -\alpha_3(\|\mathbf{x}\|, \hat{\boldsymbol{\theta}}) + \delta_V \\ & \dot{h}_a(\mathbf{x}, \hat{\boldsymbol{\psi}}, \mathbf{u}) \geq 0 \\ & u \leq u_{max} + \delta_p \\ & u \geq -u_{max} - \delta_p \\ & \dot{\hat{\boldsymbol{\theta}}} = \Gamma_1 \left(\frac{\partial V_a}{\partial \mathbf{x}}(\mathbf{x}, \hat{\boldsymbol{\theta}}) \mathbf{F}(\mathbf{x}) \right)^\top \\ & \dot{\hat{\boldsymbol{\psi}}} = -\Gamma_2 \left(\frac{\partial h_a}{\partial \mathbf{x}}(\mathbf{x}, \hat{\boldsymbol{\theta}}) \mathbf{F}(\mathbf{x}) \right)^\top \end{aligned}$$

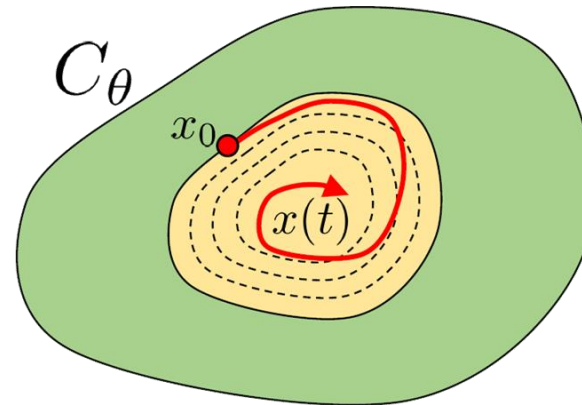


- **Adaptive Control Barrier Functions** offer solution for safety in the presence of parametric uncertainty
- Adaptive set invariance faces challenges not encountered by traditional adaptive stabilization methods
- Stabilization and safety with adaptation can be achieved simultaneously using aCLFs and aCBFs

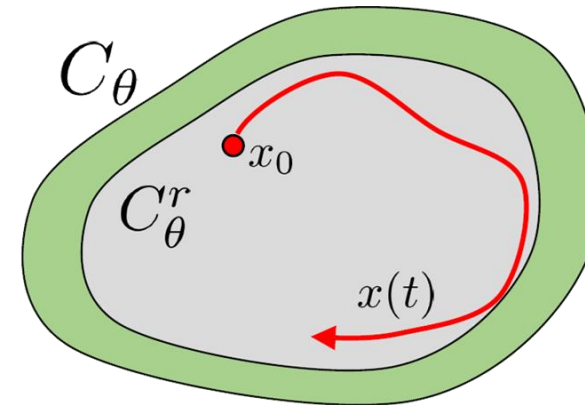


Robust Adaptive Control Barrier Functions: An Adaptive & Data-Driven Approach to Safety (Extended Version)

Brett T. Lopez, Jean-Jacques E. Slotine, Jonathan P. How
 arXiv preprint arXiv:2003.10028, 2020.



(a) Safe set with adaptive control barrier functions (aCBFs).



(b) Safe set with robust adaptive control barrier functions (RaCBFs).

Thank You!

Adaptive Safety with Control Barrier Functions

Andrew Taylor Aaron Ames