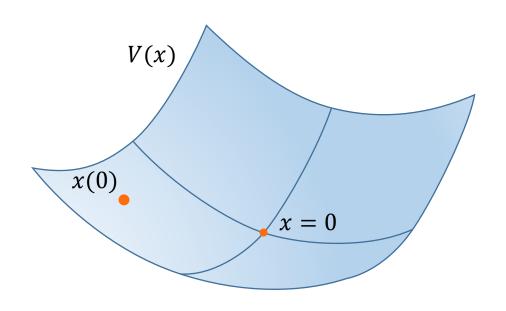


Control Lyapunov functions



• Dynamics: $x \in \mathbb{R}^n$ and $u \in \mathbb{R}^m$

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

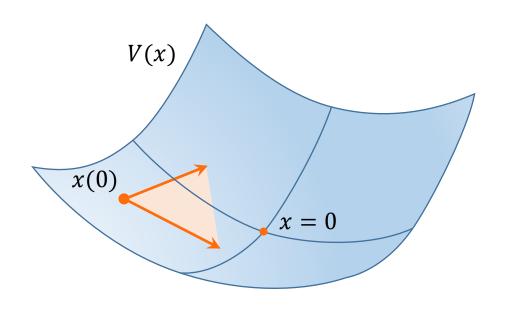
• Lyapunov: $V: X \to \mathbb{R}_+$, satisfying:

$$c_1 ||x||^2 \le V(x) \le c_2 ||x||^2$$

 $\inf_{u \in U} \dot{V}(x, u) \le -\alpha V(x)$ [1,2]

^[2] R. A. Freeman and P. V. Kokotovic. Inverse optimality in robust stabilization. SIAM journal on control and optimization, 34(4):1365–1391, 1996.

Control Lyapunov functions



• Dynamics: $x \in \mathbb{R}^n$ and $u \in \mathbb{R}^m$

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

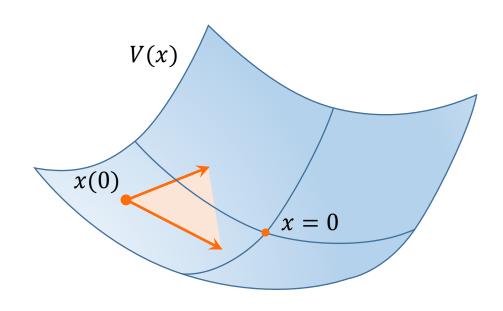
• Lyapunov: $V: X \to \mathbb{R}_+$, satisfying:

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$$\inf_{u \in U} \dot{V}(x, u) \le -\alpha V(x)$$
[1,2]

^[2] R. A. Freeman and P. V. Kokotovic. Inverse optimality in robust stabilization. SIAM journal on control and optimization, 34(4):1365–1391, 1996.

Control Lyapunov functions



[3] **CLF-QP**:

$$u(x) = \operatorname{argmin} \|u - u_{des}(x)\|^2$$

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

• Dynamics: $x \in \mathbb{R}^n$ and $u \in \mathbb{R}^m$

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

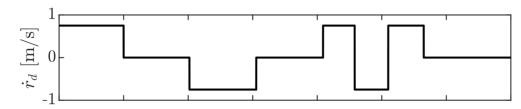
• Lyapunov: $V: X \to \mathbb{R}_+$, satisfying:

$$c_1 ||x||^2 \le V(x) \le c_2 ||x||^2$$
$$\inf_{u \in U} \dot{V}(x, u) \le -\alpha V(x)$$

Stabilizing set of controllers

Baseline Experiments

Tracking linear velocity commands



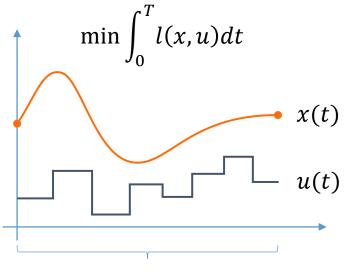
CLF-QP:

$$u(x) = \operatorname{argmin} \|u\|^2$$

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

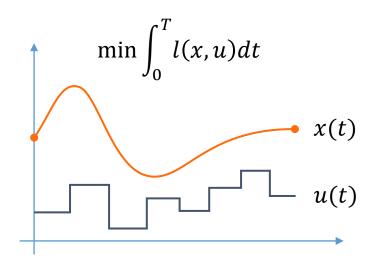


Nonlinear Model Predictive Control



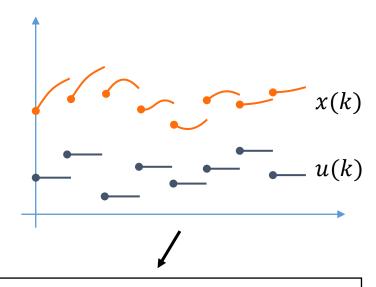
Prediction horizon

Nonlinear Model Predictive Control



Discretization (Direct multiple shooting) [4]

$$x_{k+1} = x_k + \int_{t_k}^{t_k + \delta t} f(x(\tau)) + g(x(\tau))u_k d\tau$$



Nonlinear optimization problem

$$\min_{X,U,S} l_N(x_N, p) + \phi(s_N) + \sum_{k=0}^{N-1} l_k(x_k, u_k, p) + \phi(s_k)$$
s.t.
$$x_0 - \hat{x} = 0,$$

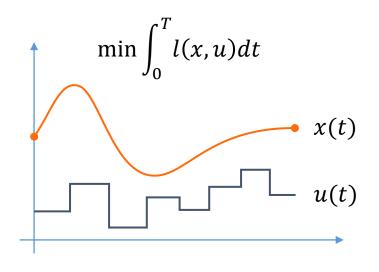
$$x_{k+1} - f_k^d(x_k, u_k) = 0, \qquad k = 0, \dots, N-1,$$

$$h_k(x_k, u_k, p) \le s_k, \qquad k = 0, \dots, N-1,$$

$$h_N(x_N, p) \le s_N,$$

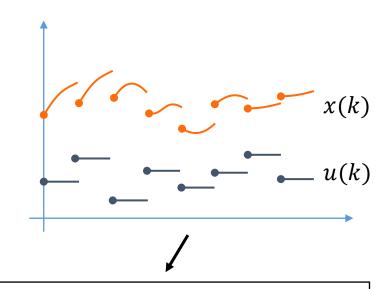
$$s_k \ge 0, \qquad k = 0, \dots, N,$$

Nonlinear Model Predictive Control



Discretization (Direct multiple shooting)

$$x_{k+1} = x_k + \int_{t_k}^{t_k + \delta t} f(x(\tau)) + g(x(\tau))u_k d\tau$$



[5]

Solved with Sequential Quadratic Programming

- 1 iteration per control update
- Quadratic approximation of the Lagrangian
- Linear approximation of dynamics and constraints

Nonlinear optimization problem

$$\min_{X,U,S} l_N(x_N, p) + \phi(s_N) + \sum_{k=0}^{N-1} l_k(x_k, u_k, p) + \phi(s_k)$$
s.t.
$$x_0 - \hat{x} = 0,$$

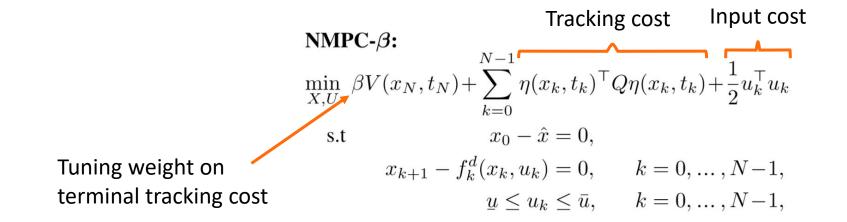
$$x_{k+1} - f_k^d(x_k, u_k) = 0, \qquad k = 0, \dots, N-1,$$

$$h_k(x_k, u_k, p) \le s_k, \qquad k = 0, \dots, N-1,$$

$$h_N(x_N, p) \le s_N,$$

$$s_k \ge 0, \qquad k = 0, \dots, N,$$

Baseline Experiments







Constraining $\dot{V}(x,u)$

Input cost

$$\begin{aligned} \min_{X,U,S} \quad \phi(s_N) + \sum_{k=0}^{N-1} \frac{1}{2} u_k^\top u_k + \phi(s_k) \\ \text{s.t} \qquad & x_0 - \hat{x} = 0, \\ x_{k+1} - f_k^d(x_k, u_k) &= 0, \qquad k = 0, \dots, N-1, \\ \underline{u} \leq u_k \leq \bar{u}, \qquad & k = 0, \dots, N-1, \\ s_k \geq 0, \qquad & k = 0, \dots, N, \end{aligned}$$

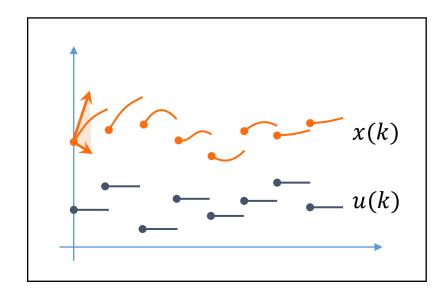
CLF-0:

 $h_{CLF}(\hat{x}, u_0) \le s_0,$

CLF stability constraint

$$h_{CLF}(x,u):$$

$$\dot{V}(x,u) \le -\alpha V(x)$$



Constraining $\dot{V}(x,u)$

Input cost

$$\min_{X,U,S} \quad \phi(s_N) + \sum_{k=0}^{N-1} \frac{1}{2} u_k^\top u_k + \phi(s_k)$$
 s.t
$$x_0 - \hat{x} = 0,$$

$$x_{k+1} - f_k^d(x_k, u_k) = 0, \qquad k = 0, \dots, N-1,$$

$$\underline{u} \leq u_k \leq \bar{u}, \qquad k = 0, \dots, N-1,$$

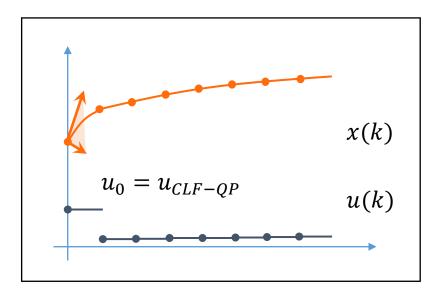
$$s_k \geq 0, \qquad k = 0, \dots, N,$$

CLF-0: $h_{CLF}(\hat{x}, u_0) \leq s_0$,

CLF stability constraint

$h_{CLF}(x,u):$ $\dot{V}(x,u) \le -\alpha V(x)$

Stabilizing, but no performance gain



Constraining $\dot{V}(x,u)$

$$\min_{X,U,S} \quad \phi(s_N) + \sum_{k=0}^{N-1} \frac{1}{2} u_k^\top u_k + \phi(s_k)$$
s.t
$$x_0 - \hat{x} = 0,$$

$$x_{k+1} - f_k^d(x_k, u_k) = 0, \qquad k = 0, \dots, N-1,$$

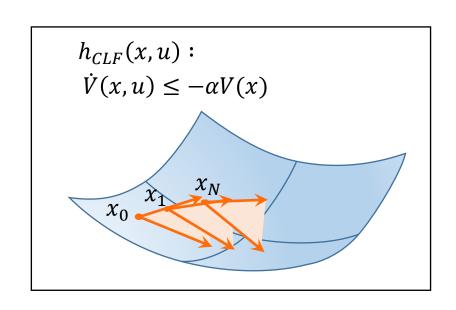
$$\underline{u} \le u_k \le \bar{u}, \qquad k = 0, \dots, N-1,$$

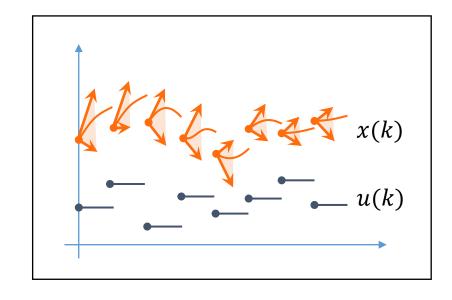
$$s_k \ge 0, \qquad k = 0, \dots, N,$$

 $CLF-0: h_{CLF}(\hat{x}, u_0) \leq s_0,$

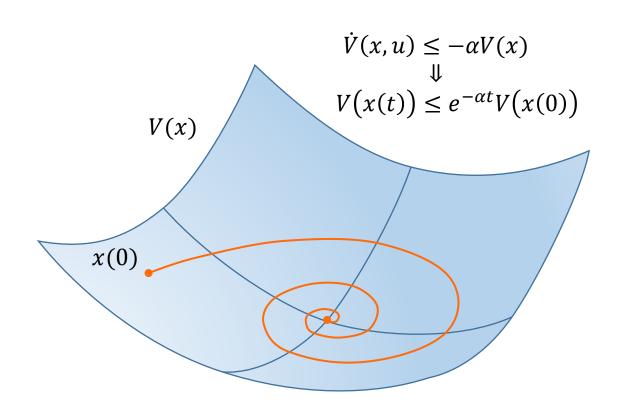
Additionally, for

CLF-ALL:
$$h_{CLF}(x_k, u_k) \leq s_k, \quad k = 1, \dots, N-1,$$

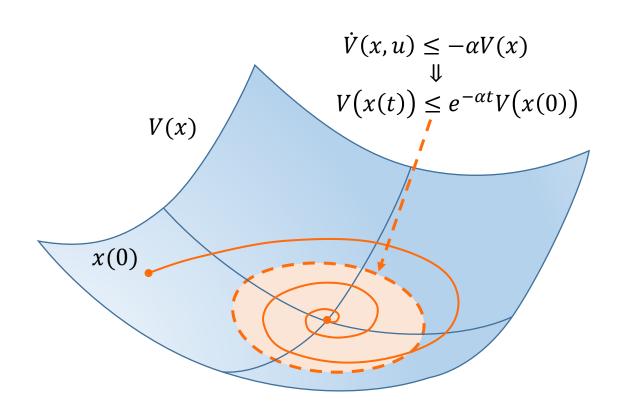




Level set constraints



Level set constraints



Level set constraints

$$\min_{X,U,S} \quad \phi(s_N) + \sum_{k=0}^{N-1} \frac{1}{2} u_k^\top u_k + \phi(s_k)$$
s.t
$$x_0 - \hat{x} = 0,$$

$$x_{k+1} - f_k^d(x_k, u_k) = 0, \qquad k = 0, \dots, N-1,$$

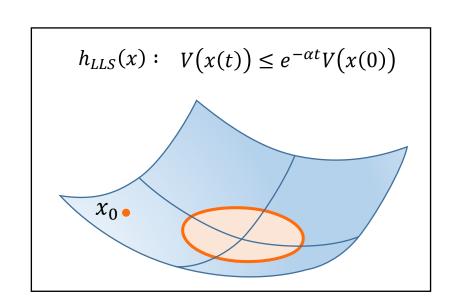
$$\underline{u} \le u_k \le \overline{u}, \qquad k = 0, \dots, N-1,$$

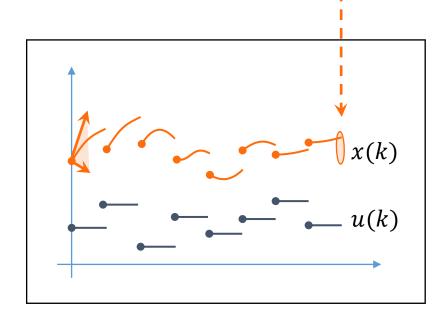
$$s_k \ge 0, \qquad k = 0, \dots, N,$$

 $CLF-0: h_{CLF}(\hat{x}, u_0) \leq s_0,$

Additionally, for

 $LLS-N: h_{LLS}(x_N, \hat{x}) \leq s_N,$





Level set constraints

$$\min_{X,U,S} \quad \phi(s_N) + \sum_{k=0}^{N-1} \frac{1}{2} u_k^\top u_k + \phi(s_k)$$
s.t
$$x_0 - \hat{x} = 0,$$

$$x_{k+1} - f_k^d(x_k, u_k) = 0, \qquad k = 0, \dots, N-1,$$

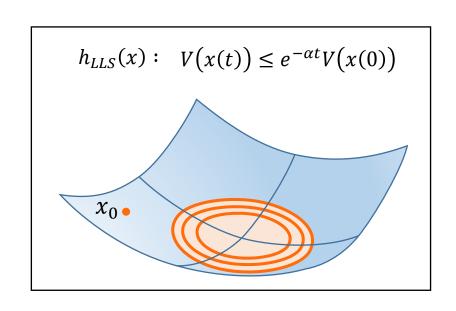
$$\underline{u} \le u_k \le \bar{u}, \qquad k = 0, \dots, N-1,$$

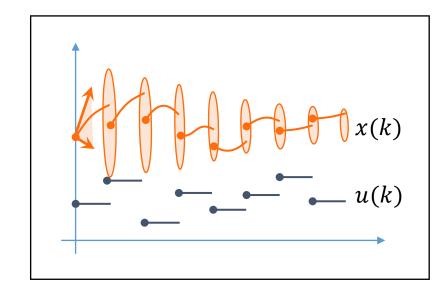
$$s_k \ge 0, \qquad k = 0, \dots, N,$$

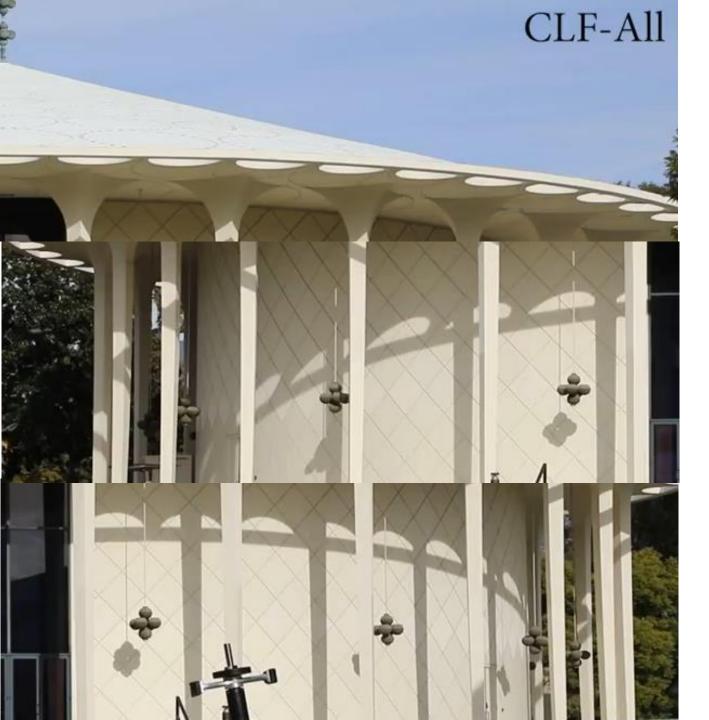
 $CLF-0: h_{CLF}(\hat{x}, u_0) \leq s_0,$

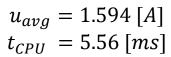
Additionally, for

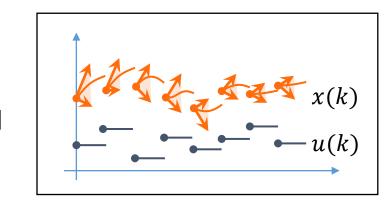
LLS-All: $h_{LLS}(x_k, \hat{x}) \leq s_k, \quad k = 1, \dots, N.$

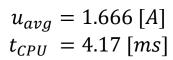


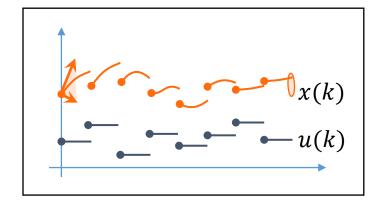




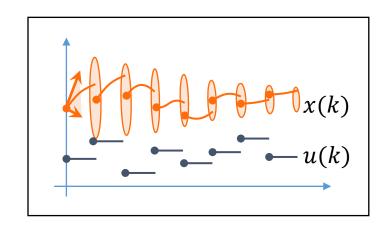








 $u_{avg} = 1.898 [A]$ $t_{CPU} = 6.13 [ms]$





Simulation $(u_{avg}[A])$

N	1	10	20	30	40	50
CLF-QP	1.085	1.085	1.085	1.085	1.085	1.085
CLF-0	1.085	1.085	1.085	1.085	1.085	1.085
CLF-All	1.085	1.072	0.952	0.849	0.794	0.769
LLS-N	1.083	0.957	0.889	0.842	0.808	0.784
LLS-All	1.083	0.956	0.887	0.839	0.805	0.782
NMPC-0.1	-	-	3.232	2.435	2.036	1.783
NMPC-1	-	3.026	2.019	1.732	1.574	1.471
NMPC-10	0.828	0.607	0.704	0.823	0.926	1.006

Main takeaways

- The CLF-NMPC controllers are stable for any horizon length (N).
- Outperform the CLF-QP formulation.
- For the baseline NMPC stability and performance are coupled and depend on tuning.
- First time for a combined approach to be demonstrated on hardware.

