

Iteration Learning Control for Uncertain Nonlinear Systems with Time Varying Output Constraint

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Speaker

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OUTLINE

Part 01 Problem Formulation

Part 02 Control Law

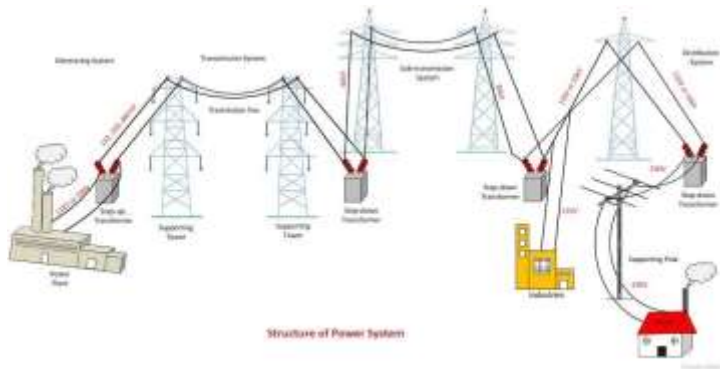
Part 03 Sketch of Stability Analysis

Part 04 Simulation Result

Part 05 Conclusion

PROBLEM FORMULATION

Motivation



Power system



Aircraft

repetitive system

safety-critical



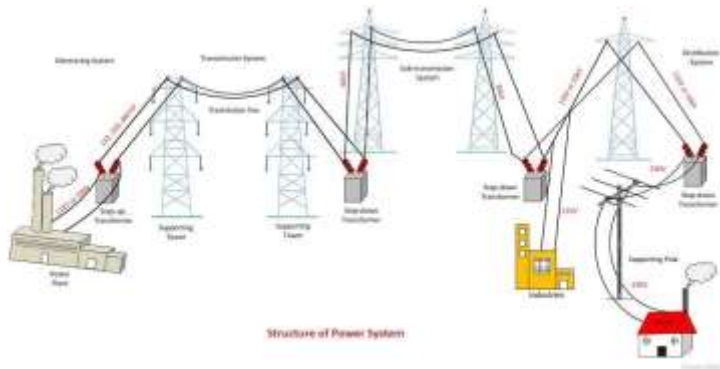
High-speed railway system



Manipulator

Motivation

How to utilize the **repetitive operation** pattern and guarantee the **safety-critical** requirement?



Power system



Aircraft

repetitive system

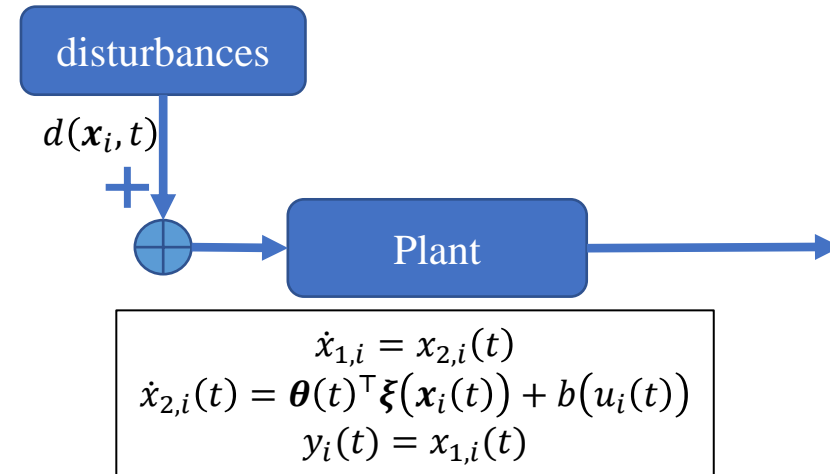
safety-critical



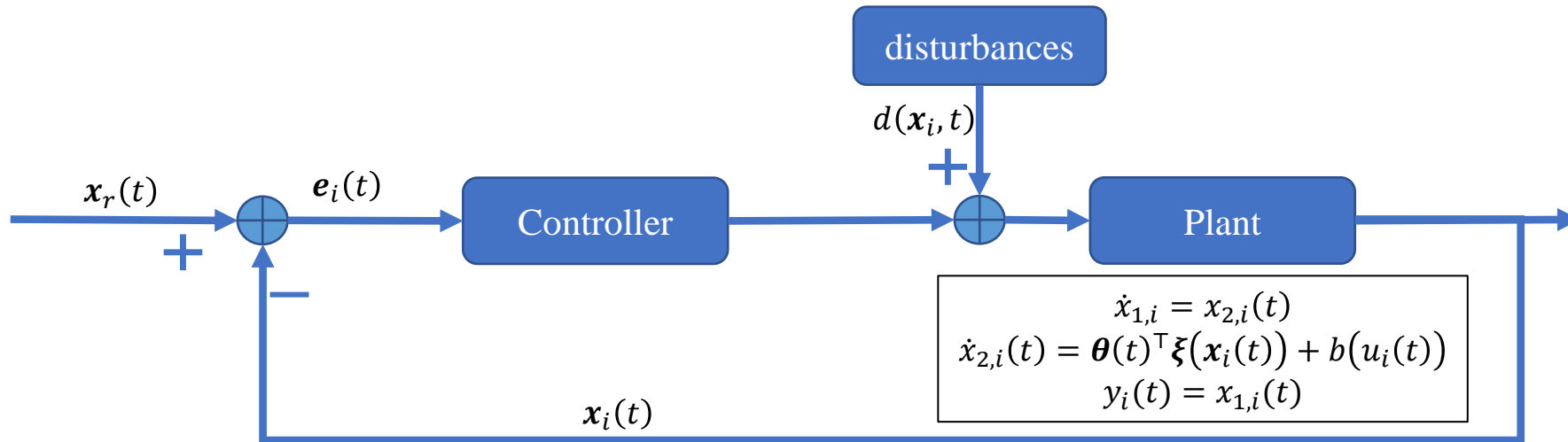
High-speed railway system



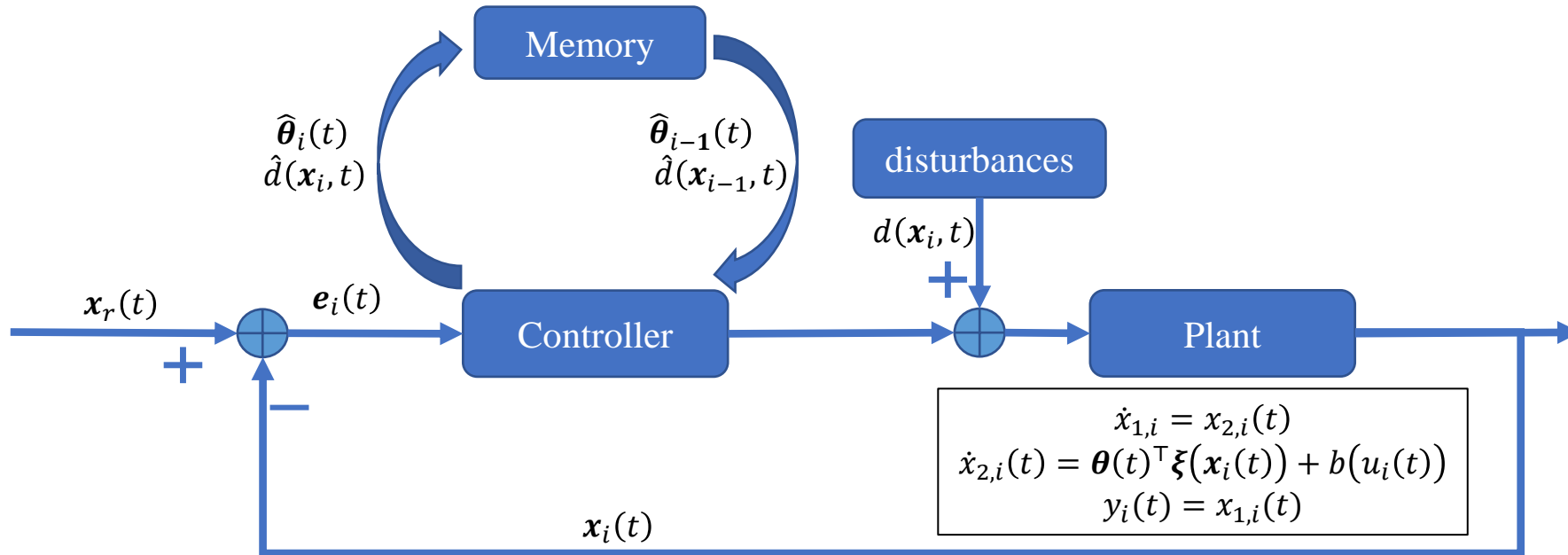
Manipulator

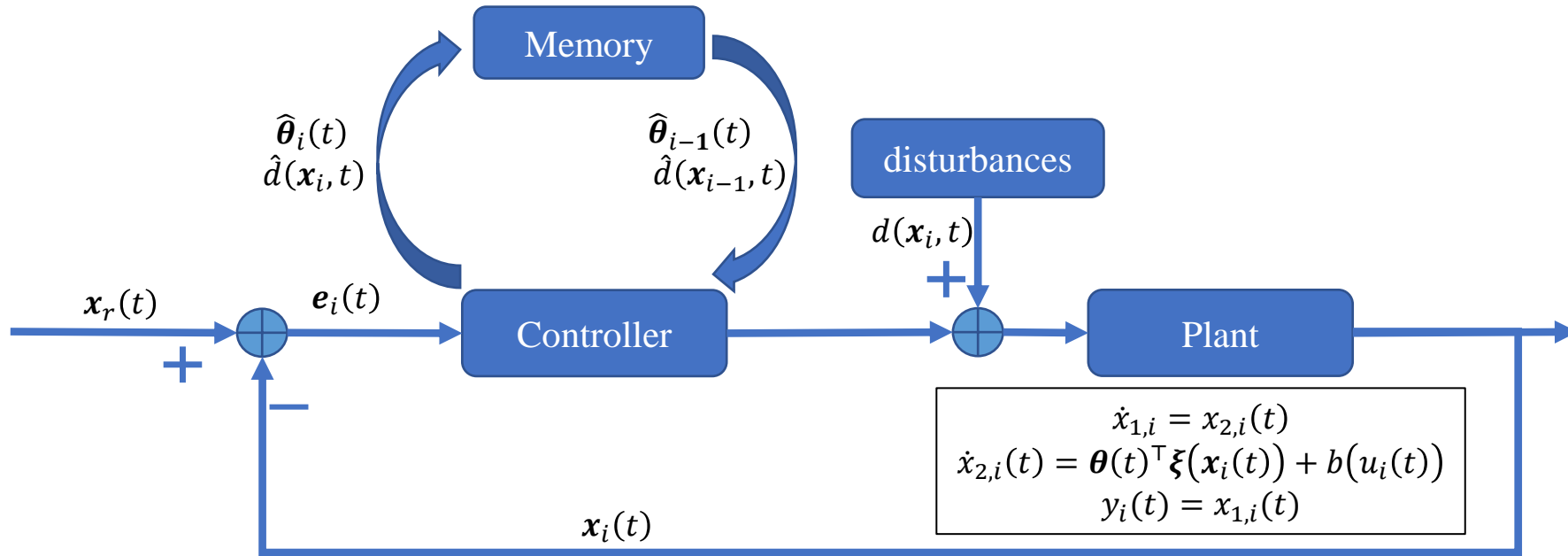


Problem Formulation



Problem Formulation





Control Objective:

Find $\{u_i\}_{i \in \mathbb{N}}$ such that $x_i(t)$ converge to $x_r(t)$ without violating the constraints $|y_i(t)| < k_b(t)$, i.e.

$$\lim_{i \rightarrow \infty} x_i(t) = x_r(t)$$

Plant

$$\begin{aligned}\dot{x}_{1,i} &= x_{2,i}(t) \\ \dot{x}_{2,i}(t) &= \boldsymbol{\theta}(t)^\top \boldsymbol{\xi}(\mathbf{x}_i(t)) + b(u_i(t) + d(\mathbf{x}_i, t)) \\ y_i(t) &= x_{1,i}(t)\end{aligned}$$

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Reference model

$$\begin{aligned}\dot{x}_{1,r}(t) &= x_{2,r}(t) \\ \dot{x}_{2,r}(t) &= \boldsymbol{\theta}(t)^\top \boldsymbol{\xi}(\mathbf{x}_r(t)) + b(u_r(t) + d(\mathbf{x}_r, t)) \\ y_r(t) &= x_{1,r}(t)\end{aligned}$$

Assumptions

- (A.1) There exists $u_r(t)$ that satisfy the reference model such that $|y_r(t)| < \varepsilon_r(t)$ holds

- (A.2) The alignment condition: $\mathbf{x}_i(0) = \mathbf{x}_{i-1}(T)$ and $\mathbf{x}_r(0) = \mathbf{x}_{r-1}(T)$

$$e_i(0) = x_r(0) - x_i(0) = x_r(T) - x_{i-1}(T) = e_{i-1}(T)$$

- (A.3) $d_i \triangleq d(\mathbf{x}_i, t)$ is locally Lipschitz continuous by a known bounded function $\varphi(\mathbf{x}_r, \mathbf{x}_i)$

$$|d(\mathbf{x}_r, t) - d(\mathbf{x}_i, t)| \leq \varphi(\mathbf{x}_r, \mathbf{x}_i) |\mathbf{x}_r - \mathbf{x}_i|$$

- (A.4) $d(\mathbf{x}_i, t)$ and $\boldsymbol{\theta}_i = [\theta_{1,i}, \theta_{2,i}, \dots, \theta_{m,i}]^\top$ are bounded, i.e. $|\theta_{l,i}|_{sup} < \bar{\theta}_l, k = 1, 2, \dots, m$ and $|d_i|_{sup} < \bar{d}_i$

CONTROL LAW

Control law

Model-based term

Compensation term

$$u_i = \frac{\partial V_{b,i}}{\partial e_{1,i}} + \gamma e_{2,i} + \frac{1}{b} [\dot{x}_{2,r} - \hat{\boldsymbol{\theta}}_i^\top \boldsymbol{\xi}_i] - \hat{d}_i + \text{sign}(p(\mathbf{e}_i)b)\varphi_i ||\mathbf{e}_i||$$

Control law

Model-based term

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$$V_{b,i} = k \frac{2\varepsilon_b^2}{\pi} \tan\left(\frac{\pi e_{1,i}^2}{2\varepsilon_b^2}\right)$$

tan-type BLF

Control law

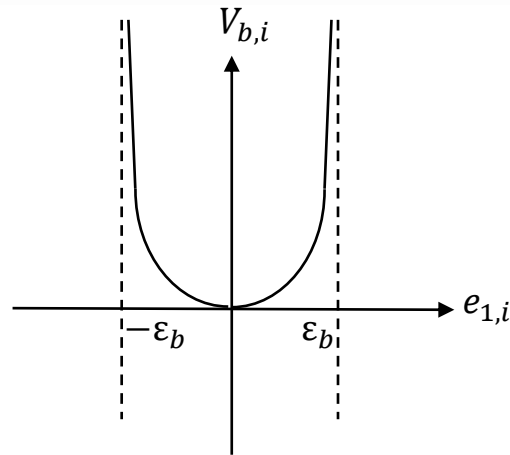
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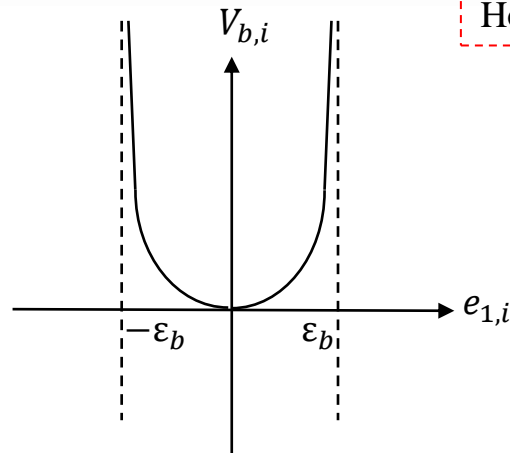
Model-based term

Compensation term

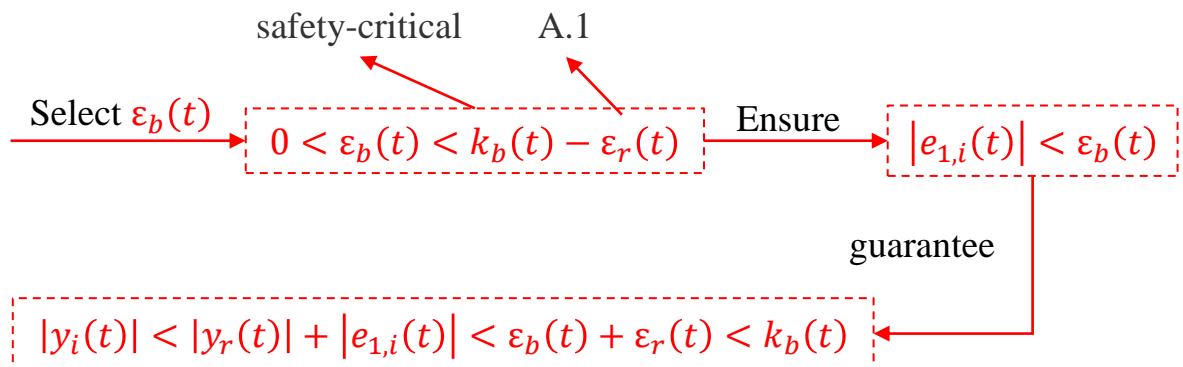
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tan-type BLF



How to satisfy $|y_i(t)| < k_b(t)$?



Control law

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$$p(\mathbf{e}_i) = 2P_{12}e_{1,i} + 2P_{22}e_{2,i}$$

simplified SISO system:

$$\dot{x}_1 = x_2$$

$$\dot{x}_2 = bv$$

control input

$$v = k \sec^2\left(\frac{\pi e_1^2}{2\varepsilon_b^2}\right) e_1 + \gamma e_2 + \frac{1}{b} \dot{x}_{2,r}$$

Control law

$$u_i = \frac{\partial V_{b,i}}{\partial e_{1,i}} + \gamma e_{2,i} + \frac{1}{b} [\dot{x}_{2,r} - \hat{\boldsymbol{\theta}}_i^\top \boldsymbol{\xi}_i] - \hat{d}_i + \text{sign}(p(e_i)b)\varphi_i ||e_i||$$

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Error dynamics:

$$\dot{e} = A_s e + B \left\{ -bk \left[\sec^2\left(\frac{\pi e_1^2}{2\varepsilon_b^2}\right) - 1 \right] e_1 \right\}$$

$$A_s = \begin{bmatrix} 0 & 1 \\ -bk & -b\gamma \end{bmatrix}, B = [0 \ 1]^\top$$

Control law

$$u_i = \frac{\partial V_{b,i}}{\partial e_{1,i}} + \gamma e_{2,i} + \frac{1}{b} [\dot{x}_{2,r} - \hat{\boldsymbol{\theta}}_i^\top \boldsymbol{\xi}_i] - \hat{d}_i + \text{sign}(p(e_i)b)\varphi_i ||e_i||$$

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$$A_s = \begin{bmatrix} 0 & 1 \\ -bk & -b\gamma \end{bmatrix}, B = [0 \ 1]^\top$$



A_s is Hurwitz

$$A_s^\top P + P A_s = -Q$$

Symmetric positive
definite matrices

$$P = \begin{bmatrix} P_{11} & P_{12} \\ P_{12} & P_{22} \end{bmatrix}, \quad Q = \begin{bmatrix} Q_{11} & Q_{12} \\ Q_{12} & Q_{22} \end{bmatrix}$$

Control law

$$u_i = \frac{\partial V_{b,i}}{\partial e_{1,i}} + \gamma e_{2,i} + \frac{1}{b} [\dot{x}_{2,r} - \widehat{\boldsymbol{\theta}}_i^\top \boldsymbol{\xi}_i] - \widehat{d}_i + \text{sign}(p(\mathbf{e}_i)b)\varphi_i \|\mathbf{e}_i\|$$

Control law

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A.3 $|d_r - d_i| \leq \varphi(x_r, x_i) |x_r - x_i|$

Control law

$$u_i = \frac{\partial V_{b,i}}{\partial e_{1,i}} + \gamma e_{2,i} + \frac{1}{b} [\dot{x}_{2,r} - \hat{\theta}_i^\top \xi_i] - \hat{d}_i + \text{sign}(p(e_i)b) \varphi_i ||e_i||$$

A.3 $|d_r - d_i| \leq \varphi(x_r, x_i) |x_r - x_i|$

Adaptive law:

$$\hat{\theta}_i = \mathcal{P}_\theta(\hat{\theta}_{i-1}) - \rho p(e_i) \xi_i \quad \hat{\theta}_0 = 0$$

$$\hat{d}_i = \mathcal{P}_d(\hat{d}_{i-1}) - \beta p(e_i) b \quad \hat{d}_0 = 0$$

$$\mathcal{P}_\theta(\theta_i) = [\mathcal{P}_\theta(\hat{\theta}_{1,i}), \dots, \mathcal{P}_\theta(\hat{\theta}_{m,i})]^\top$$

Projection operations:

$$\mathcal{P}_\theta(\hat{\theta}_{l,i}) = \begin{cases} \hat{\theta}_{l,i}, & |\hat{\theta}_{l,i}| \leq \bar{\theta}_l, \\ \text{sign}(\hat{\theta}_{l,i}) \bar{\theta}_l, & |\hat{\theta}_{l,i}| > \bar{\theta}_l, \end{cases} \quad l = 1, \dots, m$$

$$\mathcal{P}_d(\hat{d}_i) = \begin{cases} \hat{d}_i, & |\hat{d}_i| \leq \bar{d}_i \\ \text{sign}(\hat{d}_i) \bar{d}_i, & |\hat{d}_i| > \bar{d}_i \end{cases}$$

Control law

$$u_i = \frac{\partial V_{b,i}}{\partial e_{1,i}} + \gamma e_{2,i} + \frac{1}{b} [\dot{x}_{2,r} - \hat{\theta}_i^\top \xi_i] - \hat{d}_i + \text{sign}(p(e_i)b)\varphi_i \|e_i\|$$

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Adaptive law:

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$$p(e_i) = 2P_{12}e_{1,i} + 2P_{22}e_{2,i}$$

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Control law

$$u_i = \frac{\partial V_{b,i}}{\partial e_{1,i}} + \gamma e_{2,i} + \frac{1}{b} [\dot{x}_{2,r} - \hat{\theta}_i^\top \xi_i] - \hat{d}_i + \text{sign}(p(e_i)b)\varphi_i \|e_i\|$$

Positive gains

$$\text{A.3 } |d_r - d_i| \leq \varphi(x_r, x_i) |x_r - x_i|$$

Adaptive law:

$$\begin{aligned} \hat{\theta}_i &= \mathcal{P}_\theta(\hat{\theta}_{i-1}) - \rho p(e_i) \xi_i & \hat{\theta}_0 &= 0 \\ \hat{d}_i &= \mathcal{P}_d(\hat{d}_{i-1}) - \beta p(e_i) b & \hat{d}_0 &= 0 \\ \mathcal{P}_\theta(\theta_i) &= [\mathcal{P}_\theta(\hat{\theta}_{1,i}), \dots, \mathcal{P}_\theta(\hat{\theta}_{m,i})]^\top \end{aligned}$$

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SKETCH OF STABILITY ANALYSIS

Theorem

For system that meets Assumptions A.1-A.4, the control law and the adaptive learning laws guarantee that

1. $\lim_{i \rightarrow \infty} ||\mathbf{e}_i(t)|| = 0, \forall t \in [0, T]$
2. $|e_{1,i}(0)| < \varepsilon_b(0)$, then $|e_{1,i}(t)| < \varepsilon_b(t) \forall t \in [0, T], i = 1, 2, \dots$

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Error dynamic

$$\dot{e}_i = g(e_i) + f(e_i)$$
$$g(e_i) = \left[e_{2,i}, -bk \sec\left(\frac{\pi e_{1,i}^2}{2\varepsilon_b^2}\right) e_{1,i} - b\gamma e_{2,i} \right]^\top, f(e_i) = \left[0, -(\theta - \hat{\theta}_i)^\top \xi - b(d_i - \hat{d}_i) - \text{sign}(p(e_i)b)b\varphi_i ||e_i|| \right]^\top$$

Sketch of Stability Analysis

Theorem

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Error dynamic

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non-negative barrier composite energy function (BCEF)

$$E_i(t) = V_{1,i} + V_{2,i} + V_{3,i}$$

$$V_{1,i} = k \frac{2\varepsilon_b^2}{\pi} \tan\left(\frac{\pi e_{1,i}^2}{2\varepsilon_b^2}\right); \quad V_{2,i} = \frac{1}{2\rho} \int_0^T (\theta - \hat{\theta}_i)^\top (\theta - \hat{\theta}_i) d\tau; \quad V_{3,i} = \frac{1}{2\beta} \int_0^T (d_i - \{\hat{d}_i\})^2 d\tau$$

Part I: Difference of BCEF

$$\Delta E_i(T) = E_i(T) - E_{i-1}(T) = \Delta V_{1,i}(T) + \Delta V_{2,i}(T) + \Delta V_{3,i}(T)$$



$$\begin{aligned} (\theta - \hat{\theta}_{i-1})^\top (\theta - \hat{\theta}_{i-1}) &\geq (\theta - \mathcal{P}_\theta(\hat{\theta}_{i-1}))^\top (\theta - \mathcal{P}_\theta(\hat{\theta}_{i-1})) \\ (d_r - d_{i-1})^2 &\geq (d_r - \mathcal{P}_d(\hat{d}_{i-1}))^2 \end{aligned}$$

Part I: Difference of BCEF

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$$\Delta V_{1,i}(T) \leq - \int_0^T \alpha e_i^\top e_i d\tau - \int_0^T p(e_i)(\theta - \hat{\theta}_i)^\top \xi_i d\tau - \int_0^T p(e_i)b(d_i - \hat{d}_i)d\tau - \int_0^T |p(e_i)b|\varphi_i |e_i| d\tau$$

$$\Delta V_{2,i}(T) \leq \int_0^T p(e_i)(\theta - \hat{\theta}_i)^\top \xi_i d\tau$$

$$\Delta V_{3,i}(T) \leq \int_0^T p(e_i)b(d_r - \hat{d}_i)d\tau$$

$$\begin{aligned} &p(e_i)b(d_r - d_i) \\ &\leq |p(e_i)b||d(x_r, t) - d(x_i, t)| \end{aligned}$$

Sketch of Stability Analysis

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$$\begin{aligned} (\theta - \hat{\theta}_{i-1})^\top (\theta - \hat{\theta}_{i-1}) &\geq (\theta - \mathcal{P}_\theta(\hat{\theta}_{i-1}))^\top (\theta - \mathcal{P}_\theta(\hat{\theta}_{i-1})) \\ (d_r - d_{i-1})^2 &\geq (d_r - \mathcal{P}_d(\hat{d}_{i-1}))^2 \end{aligned}$$

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$$\Delta V_{3,i}(T) \leq \int_0^T p(e_i)b(d_r - \hat{d}_i)d\tau$$

$$\begin{aligned} &p(e_i)b(d_r - d_i) \\ &\leq |p(e_i)b||d(x_r, t) - d(x_i, t)| \end{aligned}$$

$$\Delta E_i(T) \leq - \int_0^T \alpha e_i^\top e_i d\tau$$

$E_i(T)$ is monotonically decreasing along iteration axis

Part II: Boundedness of $E_1(t)$ and Finiteness of $E_i(t)$

$$\dot{E}_i(t) = \dot{V}_{1,i} + \dot{V}_{2,i} + \dot{V}_{3,i}$$

Part II: Boundedness of $E_1(t)$ and Finiteness of $E_i(t)$

$$\dot{E}_i(t) = \dot{V}_{1,i} + \dot{V}_{2,i} + \dot{V}_{3,i}$$

For iteration $i = 1$

- $\dot{V}_{1,1} \leq -\alpha e_1^\top e_1 - p(e_1)(\theta + p(e_1)\xi_1)^\top \xi_1 - p(e_1)b(d_1 + p(e_1)b) - |p(e_1)b|\varphi_1||e_1||$
- $\dot{V}_{2,1} \leq \frac{1}{2\rho}|\theta|^2 + \frac{\rho}{2}p(e_1)^2|\xi_1|^2 + p(e_1)\xi_1\theta$
- $\dot{V}_{3,1} \leq \frac{1}{2\beta}d_r^2 + \frac{\beta}{2}p(e_1)^2b^2 + p(e_1)bd_r$

finite

$$\dot{E}_1(t) \leq -\alpha e_1^\top e_1 + \frac{1}{2\rho}|\theta|^2 + \frac{1}{2\beta}d_r^2 - \frac{\rho}{2}p(e_1)^2|\xi_1|^2 - \frac{\beta}{2}p(e_1)^2b^2 < \infty$$

Part II: Boundedness of $E_1(t)$ and Finiteness of $E_i(t)$

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$$\dot{E}_1(t) \leq -\alpha e_1^\top e_1 + \frac{1}{2\rho}|\theta|^2 + \frac{1}{2\beta}d_r^2 - \frac{\rho}{2}p(e_1)^2|\xi_1|^2 - \frac{\beta}{2}p(e_1)^2b^2 < \infty$$

For iteration $i > 1$

- $\dot{V}_{1,i} \leq -\alpha e_i^\top e_i - p(e_i)(\theta - \hat{\theta}_i)^\top \xi_i - p(e_i)b(d_i - \hat{d}_i) - |p(e_i)b|\varphi_i||e_i||$
- $\dot{V}_{2,i} = \frac{1}{2\rho}[\|\theta\|^2 - 2\theta^\top \mathcal{P}_\theta(\hat{\theta}_{i-1}) + \|\mathcal{P}_\theta(\hat{\theta}_{i-1})\|^2] + p(e_i)[\theta - (\mathcal{P}_\theta(\hat{\theta}_{i-1}) - p(e_i)\xi_i)]^\top \xi_i - \frac{\rho}{2}p(e_i)^2\|\xi_i\|^2$
- $\dot{V}_{3,i} = \frac{1}{2\beta}[d_r^2 - 2d_r\mathcal{P}(\hat{d}_{i-1}) + \mathcal{P}(\hat{d}_{i-1})^2] + 2\beta p(e_i)bd_r - 2\beta p(e_i)b\mathcal{P}(\hat{d}_{i-1}) + \beta^2 p(e_i)^2b^2$

$$\dot{E}_i(t) \leq \frac{C_1}{2\rho} + \frac{C_2}{2\beta} < \infty$$

Sketch of Stability Analysis

Part II: Boundedness of $E_1(t)$ and Finiteness of $E_i(t)$

$$\dot{E}_i(t) = \dot{V}_{1,i} + \dot{V}_{2,i} + \dot{V}_{3,i}$$

For iteration $i = 1$

- $\dot{V}_{1,1} \leq -\alpha e_1^\top e_1 - p(e_1)(\theta + p(e_1)\xi_1)^\top \xi_1 - p(e_1)b(d_1 + p(e_1)b) - |p(e_1)b|\varphi_1||e_1||$
- $\dot{V}_{2,1} \leq \frac{1}{2\rho}|\theta|^2 + \frac{\rho}{2}p(e_1)^2|\xi_1|^2 + p(e_1)\xi_1\theta$
- $\dot{V}_{3,1} \leq \frac{1}{2\beta}d_r^2 + \frac{\beta}{2}p(e_1)^2b^2 + p(e_1)bd_r$

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$$\dot{E}_1(t) \leq -\alpha e_1^\top e_1 + \frac{1}{2\rho}|\theta|^2 + \frac{1}{2\beta}d_r^2 - \frac{\rho}{2}p(e_1)^2|\xi_1|^2 - \frac{\beta}{2}p(e_1)^2b^2 < \infty$$

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$$\dot{E}_i(t) < \infty \forall i \in N$$

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$$t \in [0, T]$$

$$|e_{1,i}(0)| < \varepsilon_b(0)$$

$$E_i(0) = V_{1,i}(e_i(0)) < \infty$$

Sketch of Stability Analysis

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Part III: Convergence of State Tracking Error and Boundedness of System Output

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- positiveness of $E_k(T)$
- finiteness of $E_1(T)$

$$\lim_{k \rightarrow \infty} \sum_{i=2}^k \int_0^T \alpha \mathbf{e}_i^\top \mathbf{e}_i d\tau = 0$$

$$\lim_{i \rightarrow \infty} \|\mathbf{e}_i(t)\| = 0, \forall t \in [0, T]$$

SIMULATION RESULT

Numerical Example

- Plant parameters

$$\begin{aligned}x_0(0) &\triangleq [x_{1,0}(0), x_{2,0}(0)]^\top = \left[-\frac{\pi}{3}, 0\right]^\top \\x_r &\triangleq [x_{1,r}, x_{2,r}]^\top = \left[\sin\left(\frac{\pi}{2}t\right), \frac{\pi}{2}\cos\left(\frac{\pi}{2}t\right)\right]^\top, t \in [0, 12] \\b &= 0.897\end{aligned}$$

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$$b = 0.897$$

- Parametric uncertainty

$$\theta(t) = \left[1.2\text{sign}\left(\sin\left(\frac{2\pi}{3}t\right)\right), 1.2\text{sign}\left(\sin\left(\frac{2\pi}{3}t\right)\right), 1.2\text{sign}\left(\sin\left(\frac{2\pi}{3}t\right)\right)\right]^\top$$

$$\xi_i = [x_{1,i}, x_{1,i}^2, x_{1,i}^3]^\top$$

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$$\xi_i = [x_{1,i}, x_{1,i}^2, x_{1,i}^3]^\top$$

- External disturbance

$$d_i = 0.2 \sin(x_{1,i}) + 0.2 \sin(20\pi t)$$

Numerical Example Result

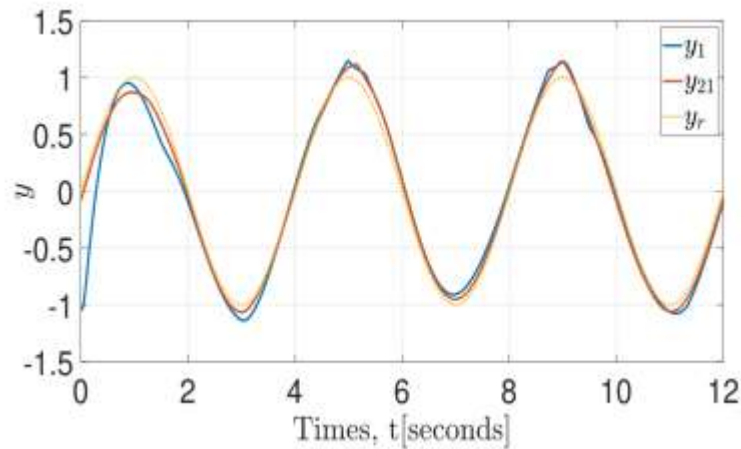
Compare Case 1: $\varepsilon_b(t) = 1.1e^{-1.5t} + 0.1$
Case 2: $\varepsilon_b(t) = 1.2$

k	γ	ρ	β	\bar{d}	$\bar{\theta}_l$
2	4	0.1	0.1	2	4

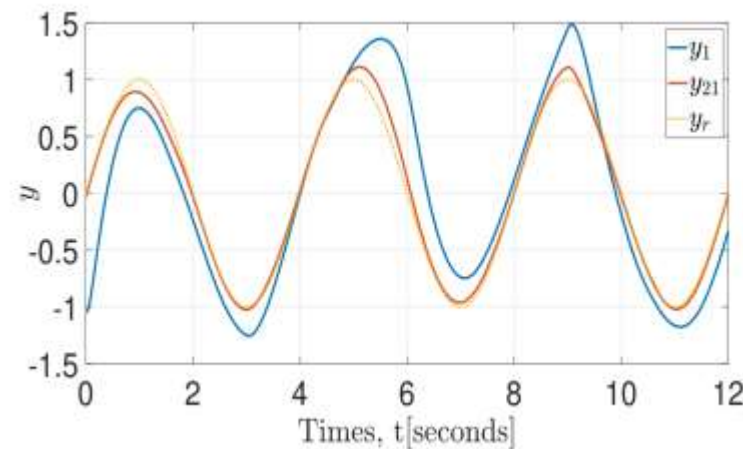
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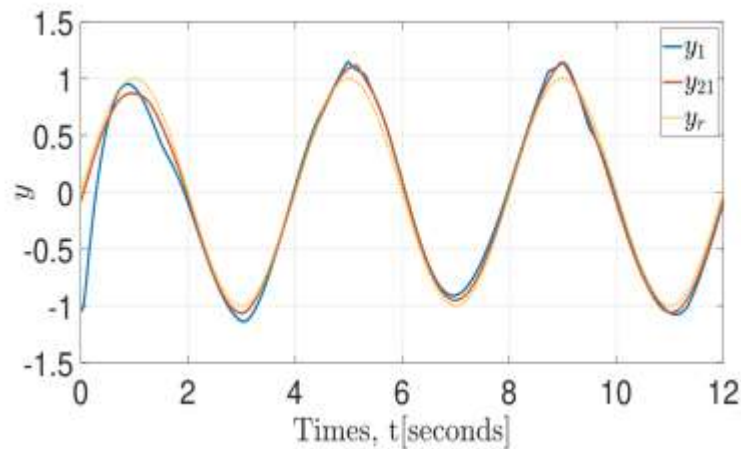


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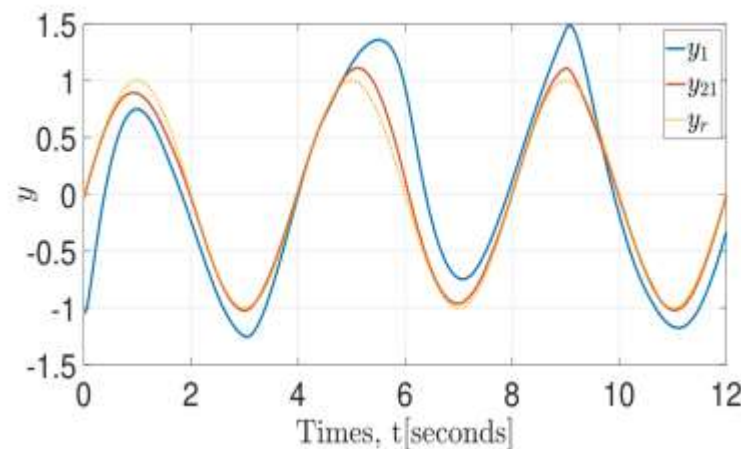
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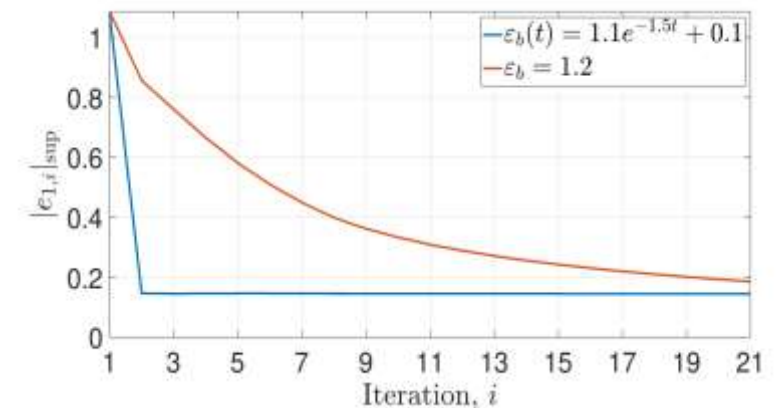
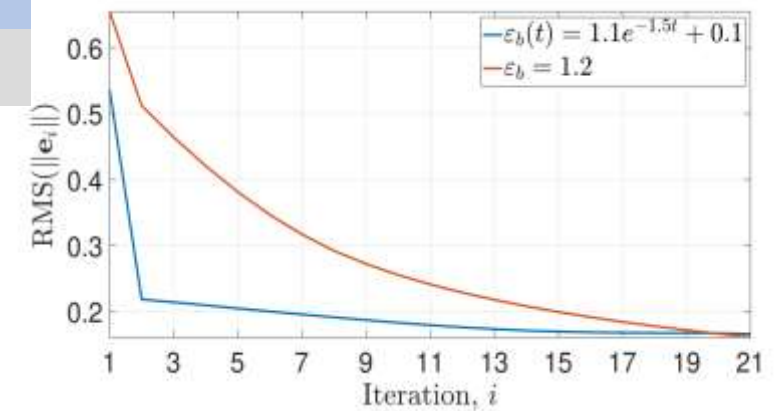
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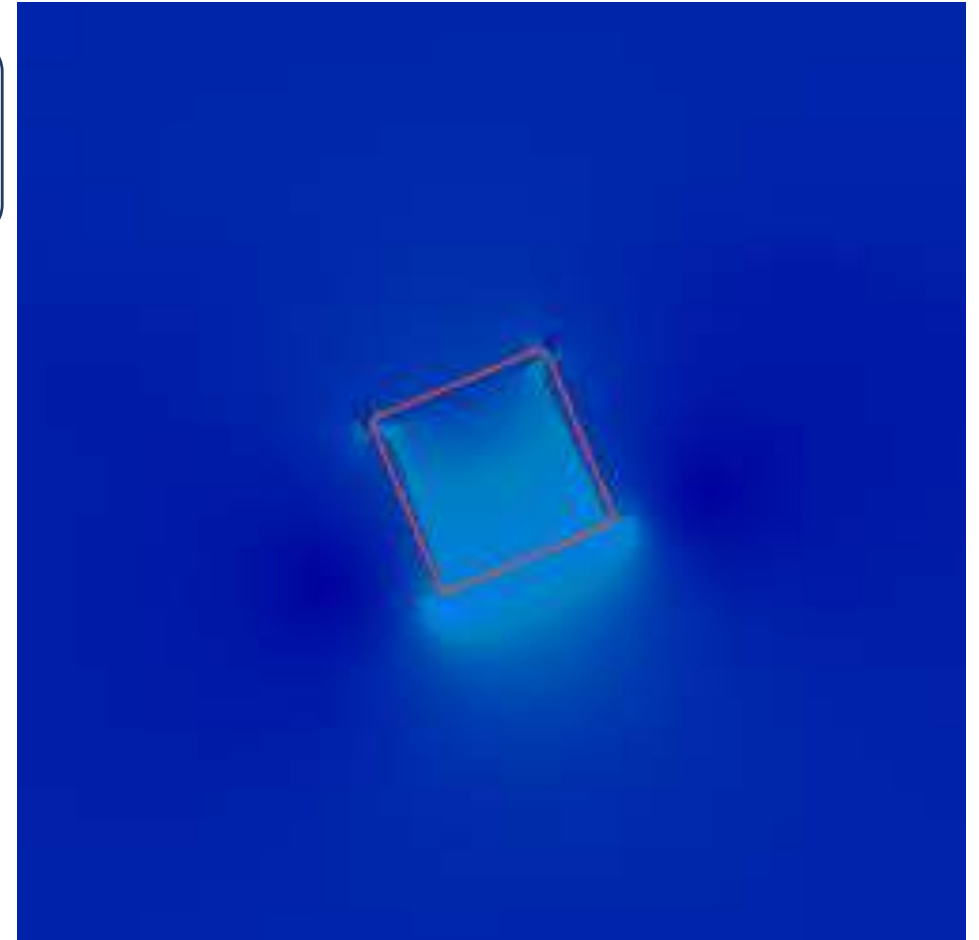


$$\varepsilon_b(t) = 1.2$$



High Fidelity Simulation*

- Plant parameters $x_0(0) \triangleq [x_{1,0}(0), x_{2,0}(0)]^\top = [0.4, 0]^\top$
 $x_r \triangleq [x_{1,r}, x_{2,r}]^\top = \left[0.4 \cos\left(\frac{\pi}{2}t\right), -\frac{\pi}{5} \sin\left(\frac{\pi}{2}t\right)\right]^\top, t \in [0, 4]$

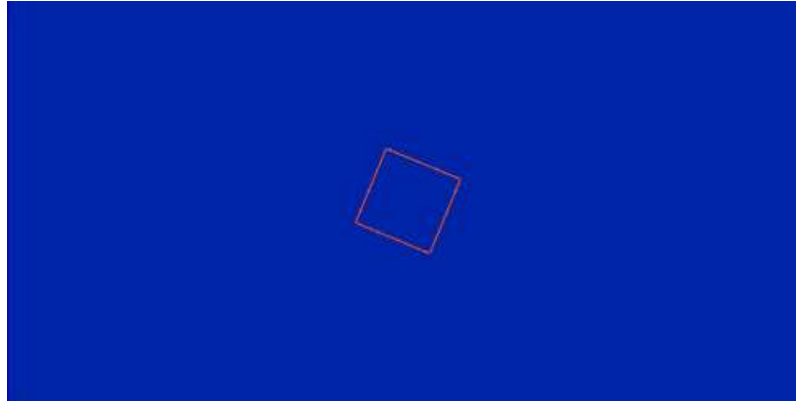


* Li, W., Chen, Y., Desbrun, M., Zheng, C., and Liu, X.(2020). Fast and scalable turbulent flow simulation with two-way coupling. ACM Transactions on Graphics, 39(4)

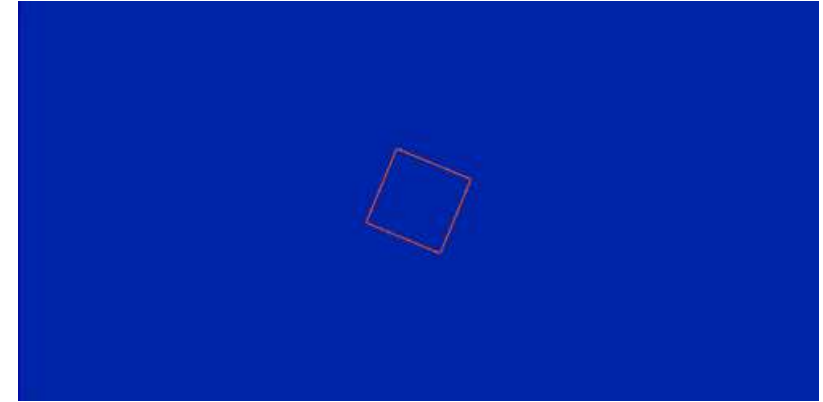
High Fidelity Simulation



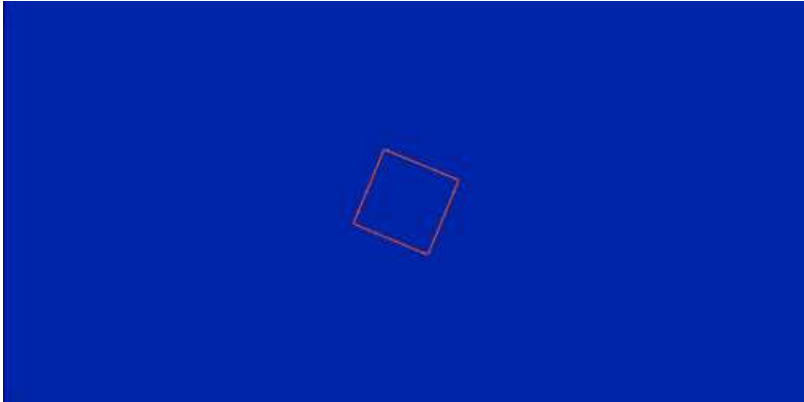
Iteration=0



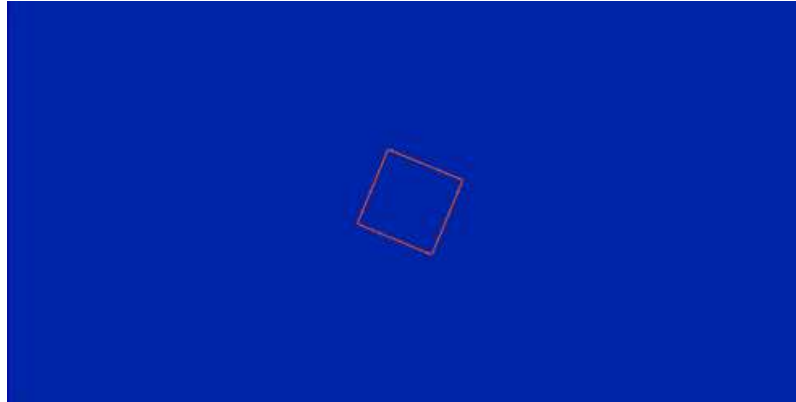
Iteration=4



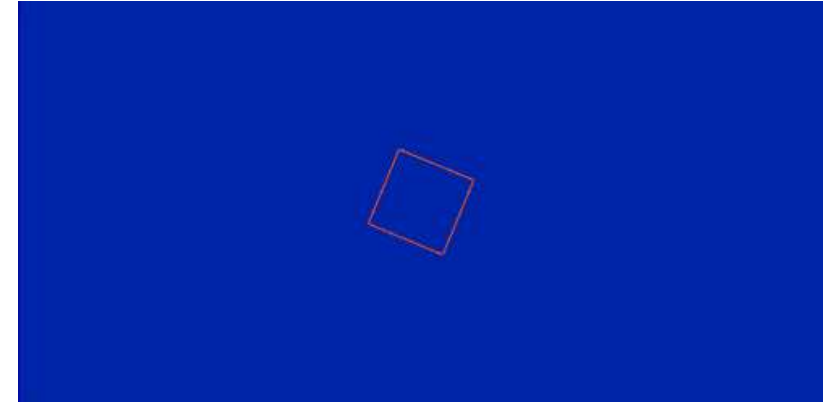
Iteration=8



Iteration=12

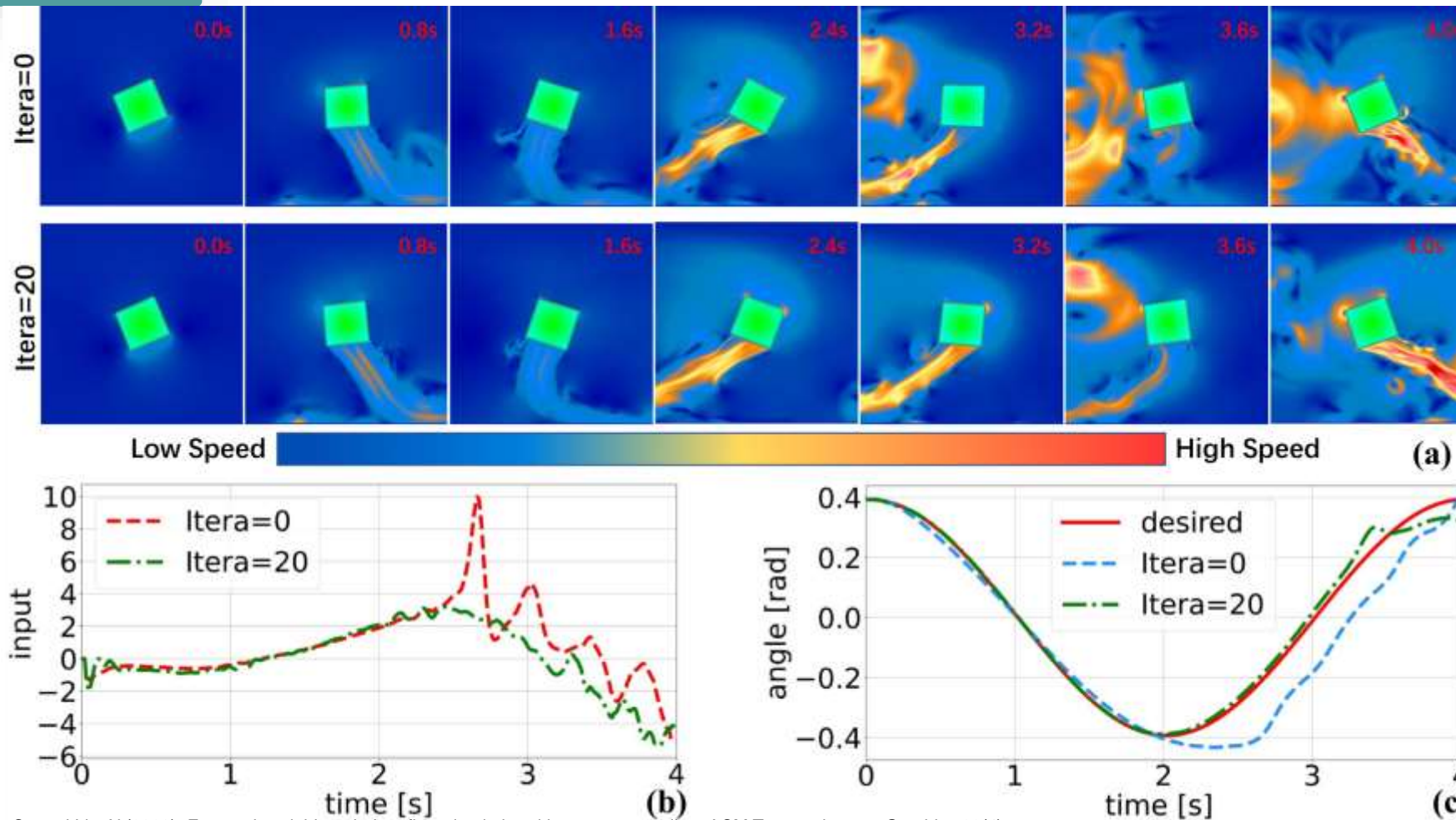


Iteration=16



Iteration=20

High Fidelity Simulation*



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CONCLUSION

Advantages:

- ✓ The plant model has time-varying output constraint
- ✓ Parametric and unstructured uncertainties are both time-varying and state-dependent
- ✓ Guarantee the asymptotic convergence of the states to their desired values

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- Simple second-order system
- Without state constraints

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Future Research Direction:

- Extension of high-order MIMO systems
- state constraints
- Applying to practical systems

THE END