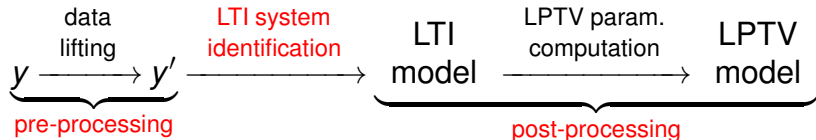


Realization and identification of autonomous linear periodically time-varying systems

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Outline



contribution

1. $O(T_p L^2)$ algorithm for LPTV system realization
 - ▶ T — # of samples
 - ▶ p — # of outputs ($\dim(y)$)
 - ▶ L — upper bound of the order
2. algorithm for LPTV maximum likelihood identification with $O(T_p L^2)$ cost per iteration

Autonomous LPTV systems

- ▶ state space representation (σ — shift operator)

$$\mathcal{B}(A, C) := \{y \mid \sigma x = Ax, y = Cx, x(1) = x_{\text{ini}} \in \mathbb{R}^n\}$$

- ▶ change of basis, *i.e.*,

$$\mathcal{B} = \mathcal{B}(A, C) = \mathcal{B}(\hat{A}, \hat{C})$$

$$\hat{A} = \sigma VAV^{-1}, \quad \hat{C} = CV^{-1}$$

- ▶ P -periodicity

$$A = \sigma^P A, \quad C = \sigma^P C, \quad V = \sigma^P V$$

Problem formulation

realization

- ▶ given: $y = (y(1), \dots, y(T))$, period P , and order n
- ▶ find: \hat{A} , \hat{C} , such that $y \in \mathcal{B}(\hat{A}, \hat{C})$

identification

- ▶ given: $y = (y(1), \dots, y(T))$, period P , and order n

$$\begin{array}{ll} \text{minimize} & \text{over } \hat{y} \text{ and } \hat{\mathcal{B}} \quad \|y - \hat{y}\|_2 \\ \text{subject to} & \hat{y} \in \hat{\mathcal{B}} \in \mathcal{L}_{0,n,P} \end{array}$$

$\mathcal{L}_{0,n,P}$ — set of autonomous LPTV systems with order at most n and period P ($0 =$ no inputs)

“lifting” operator

$$(y(1), \dots, y(T)) = y \mapsto y' = (y'(1), \dots, y'(T')), \quad T' := \lfloor T/P \rfloor$$

$$y' = \text{lift}_P(y) = \left(\begin{array}{c} \left[\begin{array}{c} y(1) \\ \vdots \\ y(P) \end{array} \right], \left[\begin{array}{c} y(P+1) \\ \vdots \\ y(2P) \end{array} \right], \dots, \left[\begin{array}{c} y((T'-1)P) \\ \vdots \\ y(T'P) \end{array} \right] \end{array} \right)$$

Theorem 1 ([BC08])

- ▶ $\mathcal{B}(A, C)$ — LPTV of order n , period P , with p outputs
- ▶ $\text{lift}_P(\mathcal{B}(A, C))$ — **LTI of order n , with $p' := pP$ outputs**

Identification of the lifted system

- ▶ $\text{lift}_P(\mathcal{B}(A, C))$ admits n th order repr. $\mathcal{B}(\Phi, \Psi)$
- ▶ $y' \mapsto (\hat{\Phi}, \hat{\Psi})$ is classical realization problem
- ▶ can be solved, e.g., by **Kung's method**

$$\underbrace{\mathcal{H}_L(y')}_{\text{Hankel}} = \underbrace{\mathcal{O}(\hat{\Phi}, \hat{\Psi})}_{\mathbf{O}} \underbrace{\mathcal{O}(\hat{\Phi}^\top, \hat{x}_{ini}^\top)}_{\mathbf{C}} \quad \begin{array}{l} \mathbf{O} \in \mathbb{R}^{Lp' \times n} \\ \mathbf{C} \in \mathbb{R}^{n \times (T'-L)} \end{array}$$

- ▶ $\hat{\Phi}^\top$ is a solution of the shift equation

$$\underline{\mathbf{O}}\hat{\Phi} = \overline{\mathbf{O}}$$

- ▶ $\hat{\Psi}$ is the first block-element of \mathbf{O}

Computation of the model parameters

Theorem 2 ([MGUP13])

- ▶ define $\hat{A} = (\hat{A}_1, \dots, \hat{A}_P)$ and $\hat{C} = (\hat{A}_1, \dots, \hat{A}_P)$ via

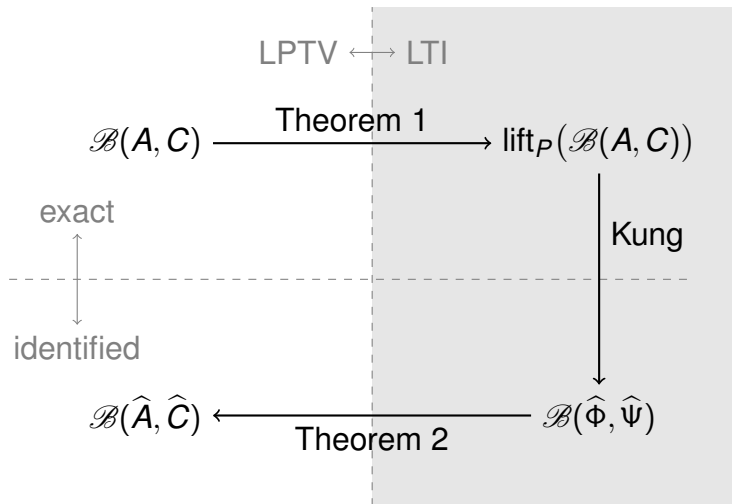
$$\begin{aligned} \hat{A}_1 = \dots = \hat{A}_{P-1} &= I_n, & \hat{A}_P &:= \hat{\Phi} \\ \text{col}(\hat{C}_1, \dots, \hat{C}_P) &:= \hat{\Psi}, & \hat{C}_i &\in \mathbb{R}^{p \times n} \end{aligned}$$

$$\text{(note that } \hat{\Psi} = \hat{A}_P \hat{A}_{P-1} \cdots \hat{A}_2 \hat{A}_1 \text{)}$$

- ▶ $\mathcal{B}(\hat{\Phi}, \hat{\Psi})$ (LTI) is equivalent to $\mathcal{B}(\hat{A}, \hat{C})$ (LPTV), *i.e.*,

$$\mathcal{B}(\hat{\Phi}, \hat{\Psi}) = \text{lift}_P(\mathcal{B}(\hat{A}, \hat{C}))$$

Summary



Modified method

- ▶ using the “transposed” lifted sequence

$$y'^{\top} := (y'^{\top}(1), \dots, y'^{\top}(T')), \quad y'^{\top}(t) \in \mathbb{R}^{1 \times p'}$$

- ▶ the Hankel matrix factorization becomes

$$\underbrace{\mathcal{H}_L(y'^{\top})}_{\text{Hankel}} = \underbrace{\mathcal{O}_L(\hat{\Phi}^{\top}, x_{\text{ini}}^{\top})}_{\mathbf{O}} \cdot \underbrace{\mathcal{O}_{T'-L+1}^{\top}(\hat{\Phi}, \hat{\Psi})}_{\mathbf{C}} \quad \begin{array}{l} \mathbf{O} \in \mathbb{R}^{L \times n} \\ \mathbf{C} \in \mathbb{R}^{n \times p(T-L)} \end{array}$$

- ▶ $\hat{\Phi}^{\top}$ is a solution of the shift equation

$$\underline{\mathbf{O}} \hat{\Phi}^{\top} = \bar{\mathbf{O}}$$

- ▶ $\hat{\Psi}^{\top}$ is the first block element of \mathbf{C}

Identification

- ▶ the SYSID problem is equivalent to

$$\begin{aligned} & \text{minimize} && \text{over } \hat{y} && \|y - \hat{y}\|_2 \\ & \text{subject to} && \text{rank}(\mathcal{H}_{n+1}(\text{lift}_P(\hat{y}^\top))) \leq n \end{aligned} \quad (\text{SLRA})$$

- ▶ (SLRA) is Hankel structured low-rank approximation
- ▶ existing methods can be used; we use the method of [MU13], which is based on the kernel representation

$$\begin{aligned} \text{rank}(\mathcal{H}_{n+1}(\text{lift}_P(\hat{y}^\top))) \leq n & \iff \\ \exists R^{1 \times (n+1)}, \quad R\mathcal{H}_{n+1}(\text{lift}_P(\hat{y}^\top)) = 0, \quad RR^\top = 1 \end{aligned}$$

Simulation setup

- ▶ the data is generated by an output error model

$$y = \bar{y} + \tilde{y}, \quad \text{where } \bar{y} \in \bar{\mathcal{B}} \in \mathcal{L}_{0,n,P} \text{ and } \tilde{y} \sim \mathbf{N}(0, s^2 I_p)$$

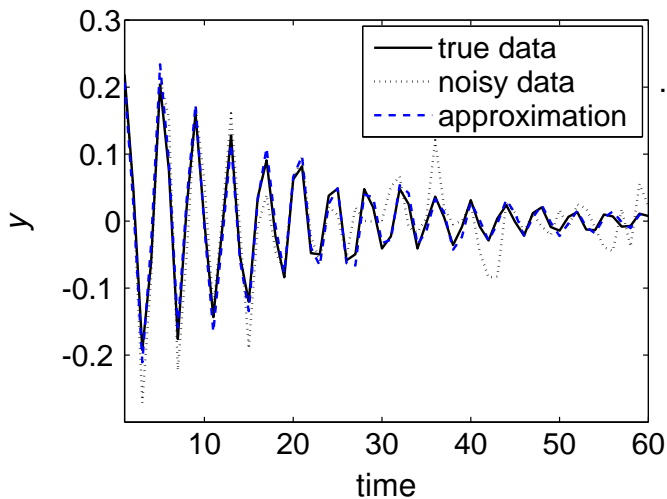
split into identification (3/4) and validation (1/4) parts

- ▶ $\bar{\mathcal{B}}$ is Mathieu oscillator—spring-mass-damper system with time-periodic spring stiffness

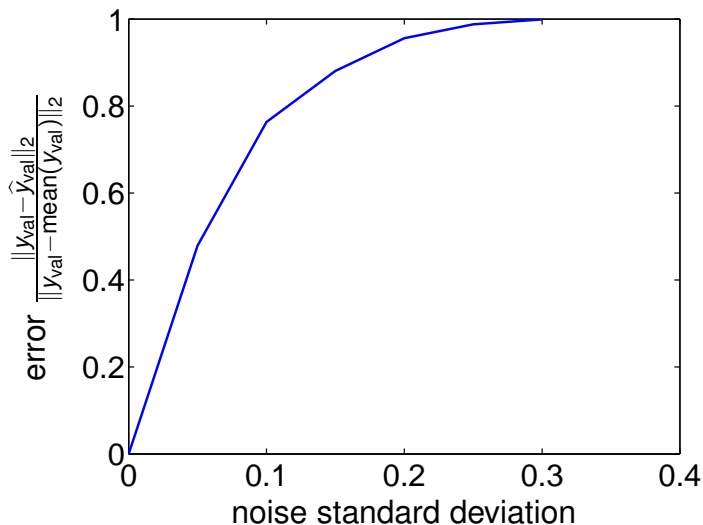
$$\bar{A}_\tau = \begin{bmatrix} 0 & 1 \\ \bar{a}_1 & \bar{a}_{2,\tau} \end{bmatrix}, \quad \bar{C}_\tau = [1 \quad 0]$$

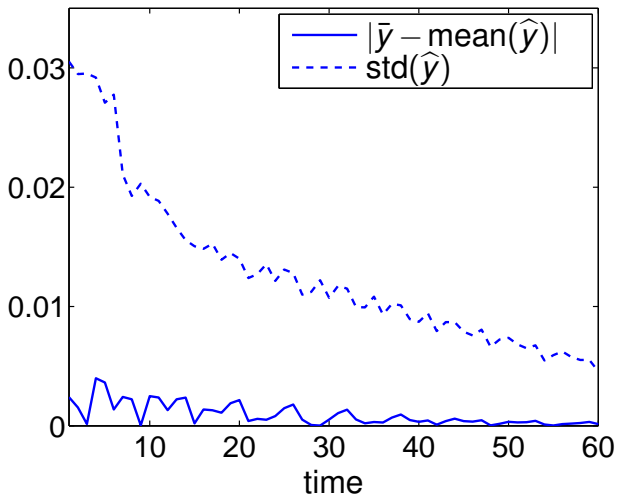
- ▶ in the example $P = 3$ and $T' = 20$

The data and its approximation



Average approximation error





Definitions




- ▶ block-Hankel matrix

$$\mathcal{H}_L(y) := \begin{bmatrix} y(1) & y(2) & y(3) & \cdots & y(T-L+1) \\ y(2) & y(3) & \ddots & & y(T-L+1) \\ y(3) & \ddots & & & \vdots \\ \vdots & & & & \\ y(L) & y(L+1) & \cdots & & y(T) \end{bmatrix}$$

- ▶ extended observability matrix

$$\mathcal{O}_L(A, C) := \begin{bmatrix} C(1) \\ C(2)A(1) \\ C(3)A(2)A(1) \\ \vdots \\ C(L)A(L-1)A(L-2)\cdots A(1) \end{bmatrix}$$

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