Linear Time-Periodic System Identification with Grouped Atomic Norm Regularization

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Grouped Atomic Norm Regularization

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Outline

Introduction

- Periodic systems, but why?
- On the shoulders of LTI systems
- Structure due to periodicity
- Enforce structure by regularization
- With pure LTI methods...
 - Least squares for the switched model
 - Low-complexity regularizers
 - Uniform order would be great

③ Our approach

- A key observation
- Grouped atomic norm regularization
- Model fitting increases in general
- Conclusion & outlook

Periodic systems, but why?

- Periodicity comes naturally in practical systems
 - Rotating dynamics (e.g., wind turbine, Allen, Sracic, et al. 2011)
 - Periodic scheduling parameters (e.g., Felici, Wingerden, and Verhaegen 2007)
 - Periodic operating trajectory (e.g., Allen and Sracic 2009)
- Linear time-periodic (LTP) systems as an intermediate step for
 - LTV systems
 - LPV systems
 - nonlinear systems along limit cycles

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The problem

LTP identification problem

Consider discrete-time stable SISO minimal LTP system

$$\begin{cases} x(t+1) = A_t x(t) + B_t u(t) \\ y(t) = C_t x(t) \end{cases}, A_t = A_{t+P}, B_t = B_{t+P}, C_t = C_{t+P}, \tag{1}$$

P is the known period.

Problem: Estimate a low-order model of (1) from input sequence u(t) and noisy output $z(t) = y(t) + w(t), w(t) \sim \mathcal{N}(0, \sigma^2)$.

On the shoulders of LTI systems

• LTP systems as structured LTI systems

Lifting

Concatenate inputs and outputs of one period

$$\tilde{u}_{\tau}(k) = \begin{bmatrix} u^{\mathsf{T}}(kP+\tau) & u^{\mathsf{T}}(kP+\tau+1) & \cdots & u^{\mathsf{T}}(kP+\tau+P-1) \end{bmatrix}^{\mathsf{T}}, \\ \tilde{y}_{\tau}(k) = \begin{bmatrix} y^{\mathsf{T}}(kP+\tau) & y^{\mathsf{T}}(kP+\tau+1) & \cdots & y^{\mathsf{T}}(kP+\tau+P-1) \end{bmatrix}^{\mathsf{T}}, \\ 0 = 0 \quad 1 \quad \text{Point the dimension } \tilde{z}_{\tau}(k) = \tilde{Q}_{\tau}(z^{P}) \tilde{z}_{\tau}(k) \text{ is LT}.$$

where $\tau = 0, 1, \dots, P-1$. Then the dynamics $\tilde{y}_{\tau}(k) = G_{\tau}(q^P)\tilde{u}_{\tau}(k)$ is LTI.

• Closely connected to subspace algorithms (Verhaegen and Yu 1995; Hench 1995)

On the shoulders of LTI systems

• LTP systems as structured LTI systems

Switching

LTP systems can be modeled as switching between P LTI systems $\{G_{\tau}(q)\}_{\tau=0}^{P-1}$.



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What's missing

LTP systems as **<u>structured</u>** LTI systems (Bittanti and Colaneri 2000).

What's the structure?

- Causality: Lifted model $\tilde{G}_{\tau}(q^P)$ has internal causality constraints.
- Uniformity: Model order for $\tilde{G}_{\tau}(q^P)$ and $G_{\tau}(q)$ should be the same for all τ .
- **Realizability:** Separately identified $\tilde{G}_{\tau}(q^P)$ and $G_{\tau}(q)$ cannot be realized to the LTP model.

Separating models and structure

Regularization method

$$\underset{\boldsymbol{\theta}}{\text{minimize }} V\left(\boldsymbol{\theta}, \begin{bmatrix} \mathbf{u} \\ \mathbf{z} \end{bmatrix} \right) + \gamma \cdot J(\boldsymbol{\theta}),$$

where θ denotes the parameters to be estimated.

 $V(\cdot, \cdot)$ How data adheres to the model

 $J(\cdot)\,$ How the model adheres to structural requirements

- Possible to use simple models (e.g., FIR models) for complex structure
- Typical structural requirements: stability, continuity, & low complexity
- In this work: to include uniformity and realizability

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A naïve idea...

• Consider FIR models of switching models $G_{\tau}(q)$

$$y(kP + \tau) = \sum_{i=1}^{N} g_i^{\tau} u(kP + \tau - i)$$

• Forgetting all structural requirements, minimize model fitting errors

minimize
$$\sum_{\tau=0}^{P-1} \sum_{k=0}^{n-1} \left[z(kP+\tau) - \sum_{i=1}^{N} g_i^{\tau} u(kP+\tau-i) \right]^2$$
 (LS)

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Low-complexity regularizers in LTI

• Enforce a low order structure on $G_{\tau}(q)$

Hankel nuclear norm regularization

$$\operatorname{rank}\left(\mathcal{H}(\mathbf{g}^{\tau})\right) = \operatorname{rank}\left(\begin{bmatrix} g_1^{\tau} & g_2^{\tau} & \cdots & g_{N-m+1}^{\tau} \\ g_2^{\tau} & g_3^{\tau} & \cdots & g_{N-m+2}^{\tau} \\ \vdots & \vdots & \ddots & \vdots \\ g_m^{\tau} & g_{m+1}^{\tau} & \cdots & g_N^{\tau} \end{bmatrix} \right) = n_x.$$

Convex surrogate of the rank function: nuclear norm $\|\mathcal{H}(\mathbf{g}^{\tau})\|_{*}$.

$$\underset{\mathbf{g}}{\text{minimize }} V_{\text{LS}}\left(\mathbf{g}, \begin{bmatrix} \mathbf{u} \\ \mathbf{z} \end{bmatrix}\right) + \sum_{\tau=1}^{P} \beta_{\tau} \left\| \mathcal{H}(\mathbf{g}^{\tau}) \right\|_{*}$$
 (Hank)

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Low-complexity regularizers in LTI

Atomic norm regularization (Shah et al. 2012)

The switching models $G_{\tau}(q)$ can be decomposed as a linear combination of stable first order models

$$G_{\tau}(q) = \sum_{w \in \mathbb{D}} c_w^{\tau} \cdot a_w(q) \approx \sum_{k=1}^{n_p} c_k^{\tau} \cdot a_{w_k}(q) := \mathbf{c}_{\tau}^T \mathbf{a}(q), \quad a_w(q) = \frac{1 - |w|^2}{q - w}$$

Then,

$$\operatorname{card}(\mathbf{c}_{\tau}) = n_x.$$

Convex surrogate of the cardinality function: l_1 norm $\|\mathbf{c}_{\tau}\|_1$, also known as the atomic norm of $G_{\tau}(q)$.

Low-complexity regularizers in LTI

minimize
$$V_{\text{LS}}\left(\mathbf{g}^{a}\mathbf{c}, \begin{bmatrix} \mathbf{u} \\ \mathbf{z} \end{bmatrix}\right) + \sum_{\tau=1}^{P} \beta_{\tau} \|\mathbf{c}_{\tau}\|_{1},$$
 (Atom)

where g^a is the truncated impulse responses of a(q).

Compared with (Hank),

Pros: Stability guarantee, better scalability

Cons: Pole location approximation, impulse response truncation

A variable-length pendulum example



Model as a discrete-time SISO LTP system from F to ψ with P = 4.

Can we get a switching LTP model with uniform order by fine tuning of β_{τ} ?

$$\ddot{\psi} = -\frac{g}{L(t)}\sin\psi + \frac{2\omega l\sin\omega t}{L(t)}\dot{\psi} + \frac{1}{mL(t)}F\cos\psi,$$
$$L(t) = L_0 + l\cos\omega t$$

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A pitfall...

... No. There is barely any consensus on the model order.



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A key observation to satisfy LTP requirements

$$G_{\tau}(q) = C(\tau)(q^{P}\mathbb{I} - \Psi_{A,\tau})^{-1}\mathcal{B}_{\tau}(q),$$

where

$$\Psi_{A,\tau} = A(\tau - 1)A(\tau - 2)\cdots A(\tau - P)$$

$$\mathcal{B}_{\tau}(q) = \sum_{i=0}^{P-1} A(\tau-1)A(\tau-2)\cdots A(\tau+i-P+1)B(\tau+i)\cdot q^{i}.$$

- The poles of $G_{\tau}(q)$ are *P*-th root of the poles of $\Psi_{A,\tau}$, which happens to be independent of τ (Bittanti 1986).
- The active set of c_{τ} is the same for all τ .

Connecting switching models

Proposed method: Grouped atomic norm regularization

Let $\mathbf{c} = [\mathbf{c}_0 \ \mathbf{c}_1 \ \cdots \ \mathbf{c}_{P-1}]$, \mathbf{c} is sparse for each column, but non-sparse or all zero for each row.

Then,

$$\operatorname{\mathsf{card}}\left(\left\|\mathbf{c}^{(k)}\right\|_{2}
ight)=n_{x}, \quad \mathbf{c}^{(k)}: \ k ext{-th row of } \mathbf{c}$$

Convex surrogate: sum-of-norms $\sum_{k=1}^{n_p} \|\mathbf{c}^{(k)}\|_2$.



Grouped atomic norm regularization

minimize
$$V_{\text{LS}}\left(\mathbf{g}^{a}\mathbf{c}, \begin{bmatrix} \mathbf{u} \\ \mathbf{z} \end{bmatrix}\right) + \gamma \sum_{k=1}^{n_{p}} \left\|\mathbf{c}^{(k)}\right\|_{2}$$
 (GAtom)

Characteristics of this estimator:

- Uniformity is guaranteed
- Realizability is promising (ongoing work)
- Low-complexity and stability maintained as in (Atom)

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Check with the pendulum example

It's working!



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Model fitting on random systems

- 100 randomly generated LTP systems
- P = 2, system order between 2 and 10
- 500 data points
- Unit Gaussian inputs
- Two noise levels: $\sigma^2 = 0.1, 0.01$
- Hyperparameter tuning by cross-validation

• Fitting metric:
$$W = 100 \cdot \left(1 - \frac{\|\mathbf{g} - \mathbf{g}_0\|_2}{\|\mathbf{g}_0 - \bar{g}\|_2}\right)$$

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Results



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Conclusion & outlook

- LTP system identification cannot be fully tackled by LTI reformulation
- Periodic structure is the key to estimating LTP systems
- Such structure can be encoded by regularization methods

Further problems:

- Realization of the grouped atomic norm estimator
- Active selection of first-order basis model

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