



Technische  
Universität  
Braunschweig



# **Model Order Reduction of Higher Order Systems**

Joint work with Peter Benner and Philip Saltenberger

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Institute for Numerical Analysis, TU Braunschweig

# Higher Order Linear Time-Invariant Systems

## Higher Order Linear Time-Invariant Systems

Given matrices  $P_j \in \mathbb{R}^{n \times n}$ ,  $0 \leq j \leq \ell$ ,  $C_j \in \mathbb{R}^{p \times n}$ ,  $0 \leq j < \ell$ ,  $B \in \mathbb{R}^{n \times m}$ ,  $D \in \mathbb{R}^{p \times m}$  and an input function  $u : [0, \infty) \rightarrow \mathbb{R}^m$ , we seek the state function  $x : [0, \infty) \rightarrow \mathbb{R}^n$  and the output function  $y : [0, \infty) \rightarrow \mathbb{R}^p$  such that

$$P_\ell \frac{d^\ell}{dt^\ell} x(t) + P_{\ell-1} \frac{d^{\ell-1}}{dt^{\ell-1}} x(t) + \cdots + P_1 \frac{d}{dt} x(t) + P_0 x(t) = Bu(t)$$

$$Du(t) + C_{\ell-1} \frac{d^{\ell-1}}{dt^{\ell-1}} x(t) + \cdots + C_1 \frac{d}{dt} x(t) + C_0 x(t) = y(t)$$

with initial conditions

$$\left. \frac{d^j}{dt^j} x(t) \right|_{t=0} = x_0^{(j)}, \quad 0 \leq j \leq \ell,$$

where  $x_0^{(j)} \in \mathbb{R}^n$ ,  $0 \leq j \leq \ell$  are given vectors.

## Transfer Function

$$G(s) = D + \sum_{j=0}^{\ell-1} C_j (P_0 + sP_1 + s^2P_2 + \cdots + s^\ell P_\ell)^{-1} B = D + \sum_{j=0}^{\ell-1} C_j (P(s))^{-1} B.$$

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# Higher Order Linear Time-Invariant Systems

## Model Order Reduction for Higher Order Linear Time-Invariant Systems

Given matrices

$$P_j \in \mathbb{R}^{n \times n}, 0 \leq j \leq \ell, C_j \in \mathbb{R}^{p \times n}, 0 \leq j < \ell, B \in \mathbb{R}^{n \times m}, D \in \mathbb{R}^{p \times m}$$

and an input function  $u : [0, \infty) \rightarrow \mathbb{R}^m$ , we seek reduced order matrices

$$\hat{P}_j \in \mathbb{R}^{r \times r}, 0 \leq j \leq \ell, \hat{C}_j \in \mathbb{R}^{p \times r}, 0 \leq j < \ell, \hat{B} \in \mathbb{R}^{r \times m}, \hat{D} \in \mathbb{R}^{p \times m}$$

with  $r \ll n$  such that

$$\begin{aligned} \hat{P}_\ell \frac{d^\ell}{dt^\ell} \hat{x}(t) + \hat{P}_{\ell-1} \frac{d^{\ell-1}}{dt^{\ell-1}} \hat{x}(t) + \cdots + \hat{P}_1 \frac{d}{dt} \hat{x}(t) + \hat{P}_0 \hat{x}(t) &= \hat{B}u(t) \\ \hat{D}u(t) + \hat{C}_{\ell-1} \frac{d^{\ell-1}}{dt^{\ell-1}} \hat{x}(t) + \cdots + \hat{C}_1 \frac{d}{dt} \hat{x}(t) + \hat{C}_0 \hat{x}(t) &= \hat{y}(t) \end{aligned}$$

with suitable initial conditions yields a transfer function  $\hat{G}(s)$  such that

$$\hat{G}(s) = G(s) + \mathcal{O}((s - s_0)^r) \text{ for some } s_0 \in \mathbb{C}.$$

# Higher Order Linear Time-Invariant Systems

## Galerkin Projection of Higher Order Linear Time-Invariant Systems

Given matrices  $P_j \in \mathbb{R}^{n \times n}$ ,  $C_j \in \mathbb{R}^{p \times n}$ ,  $B \in \mathbb{R}^{n \times m}$ ,  $D \in \mathbb{R}^{p \times m}$ , find a matrix  $V \in \mathbb{R}^{n \times r}$  with orthonormal columns with  $r \ll n$  and construct

$$\begin{aligned}\hat{P}_j &= V^T P_j V \in \mathbb{R}^{r \times r}, & \hat{B} &= V^T B \in \mathbb{R}^{r \times m}, \\ \hat{C}_j &= C_j V \in \mathbb{R}^{p \times r}, & \hat{D} &= D \in \mathbb{R}^{p \times m},\end{aligned}$$

such that

$$\hat{G}(s) = G(s) + \mathcal{O}((s - s_0)^r) \text{ for some } s_0 \in \mathbb{C}.$$

# Higher Order Linear Time-Invariant Systems

## Standard approach: Linearization

Consider associated matrix polynomial  $P(\lambda) = \lambda^\ell P_\ell + \lambda^{\ell-1} P_{\ell-1} + \cdots + \lambda P_1 + P_0 \in \Pi_\ell^n$  and convert it into  $\lambda \mathcal{E} + \mathcal{A} \in \Pi_1^{\ell n}$  with the same eigenvalues.

## Outline

- Illustrative examples
- Approach 1: MOR for higher order system by Freund (2005)
- (Approach 2: MOR for higher order system by Li, Bao, Lin, Wei (2011))
- New developments in linearization of matrix polynomials
  - Generalization of companion form linearization  $\mathbb{L}_1$
  - Block Kronecker linearizations  $\mathbb{G}_{r+1}$
- Higher order LTI systems and block Kronecker linearizations

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## Illustrative examples

### Gyroscopic system $P(\lambda) \in \Pi_2^n$

$$P(\lambda) = \lambda^2 M + \lambda G + K, \quad M = M^T, G = -G^T, K = K^T, \quad M, G, K \in \mathbb{R}^{n \times n}.$$

Such problems arise, for example, in finite element discretization in structural analysis and in the elastic deformation of anisotropic materials. They are used to model vibrations of spinning structures such as the simulation of tire noise, helicopter rotor blades, or spin-stabilized satellites with appended solar panels or antennas.

### Robot $P(\lambda) \in \Pi_4^n$

$$P(\lambda) = \lambda^4 P_4 + \lambda^3 P_3 + \lambda^2 P_2 + \lambda P_1 + P_0, \quad P_i = (-1)^i P_i^T, \quad P_i \in \mathbb{R}^{n \times n}, i = 0, \dots, 4.$$

Such problems arise, e.g., from the model of a robot with electric motors in the joints.

### T-even matrix polynomials

For both examples:  $P(\lambda) = P(-\lambda)^T$ .

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## Back to Higher Order Linear Time-Invariant Systems

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$$Du(t) + C_{\ell-1} \frac{d^{\ell-1}}{dt^{\ell-1}} x(t) + \cdots + C_1 \frac{d}{dt} x(t) + C_0 x(t) = y(t)$$

Let

$$z(t) = \begin{bmatrix} x(t) \\ \frac{d}{dt} x(t) \\ \vdots \\ \frac{d^{\ell-1}}{dt^{\ell-1}} x(t) \end{bmatrix}, \quad \mathcal{B}_F = \begin{bmatrix} 0 \\ \vdots \\ 0 \\ B \end{bmatrix}, \quad \mathcal{A}_F = \begin{bmatrix} 0 & -I_n & 0 & \cdots & 0 \\ 0 & 0 & -I_n & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & 0 & -I_n \\ P_0 & P_1 & P_2 & \cdots & P_{\ell-1} \end{bmatrix},$$

$$\mathcal{E}_F = \begin{bmatrix} I_{(\ell-1)n} \\ P_\ell \end{bmatrix}, \quad \mathcal{C}_F = [C_0 \ C_1 \ \cdots \ C_{\ell-1}], \quad \mathcal{D}_F = D.$$

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# Approach 1

[Freund 2005]

## Approach 1: Linearization via the first companion form

The higher order system is equivalent to the first order system

$$\mathcal{E}_F \frac{d}{dt} z(t) + \mathcal{A}_F z(t) = \mathcal{B}_F u(t)$$

$$y(t) = \mathcal{D}_F u(t) + \mathcal{C}_F z(t)$$

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where

$$z(t) = \begin{bmatrix} x(t) \\ \frac{d}{dt} x(t) \\ \vdots \\ \frac{d^{\ell-1}}{dt^{\ell-1}} x(t) \end{bmatrix}, z_0 = \begin{bmatrix} x_0^{(0)} \\ x_0^{(1)} \\ \vdots \\ x_0^{(\ell-1)} \end{bmatrix}, \mathcal{B}_F = \begin{bmatrix} 0 \\ \vdots \\ 0 \\ B \end{bmatrix}, \mathcal{A}_F = \begin{bmatrix} 0 & -I_n & 0 & \cdots & 0 \\ 0 & 0 & -I_n & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & 0 & -I_n \\ P_0 & P_1 & P_2 & \cdots & P_{\ell-1} \end{bmatrix},$$

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- $\mathcal{E}_F, \mathcal{A}_F \in \mathbb{R}^{\ell n \times \ell n}, \mathcal{B}_F \in \mathbb{R}^{\ell n \times m}$  are large and (block-) sparse.
- $\lambda \mathcal{E}_F + \mathcal{A}_F$  does not inherit any structure from  $P(\lambda)$ ,  
that is, e.g.,  $P(\lambda) = P(\lambda)^T$  does not imply that  $(\lambda \mathcal{E}_F + \mathcal{A}_F)^T = \lambda \mathcal{E}_F + \mathcal{A}_F$ .

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# Approach 1

[Freund 2005]

- Rewrite  $G(s) = \mathcal{D}_F + \mathcal{C}_F(s\mathcal{E}_F + \mathcal{A}_F)^{-1}\mathcal{B}_F$  for  $s_0 \in \mathbb{C}$  such that  $s_0\mathcal{E}_F + \mathcal{A}_F$  is nonsingular as

$$G(s) = \mathcal{D}_F + \mathcal{C}_F(I + (s - s_0)\mathcal{M}_F)^{-1}\mathcal{R}_F$$

with

$$\mathcal{M}_F = (s_0\mathcal{E}_F + \mathcal{A}_F)^{-1}\mathcal{E}_F \in \mathbb{C}^{\ell n \times \ell n}, \quad \mathcal{R}_F = (s_0\mathcal{E}_F + \mathcal{A}_F)^{-1}\mathcal{B}_F \in \mathbb{C}^{\ell n \times m}.$$

- Compute orthonormal basis of  $\mathcal{K}_s(\mathcal{M}_F, \mathcal{R}_F) = \text{span}\{\mathcal{R}_F, \mathcal{M}_F\mathcal{R}_F, \dots, \mathcal{M}_F^{s-1}\mathcal{R}_F\}$ .
- Let  $\mathcal{W}$  be the matrix representing the basis.
- Generate reduced order system

$$\hat{\mathcal{E}} \frac{d}{dt} \hat{z}(t) + \hat{\mathcal{A}} \hat{z}(t) = \hat{\mathcal{B}} u(t)$$

$$\hat{y}(t) = \mathcal{D} u(t) + \hat{\mathcal{C}} \hat{z}(t)$$

with  $\hat{\mathcal{E}} = \mathcal{W}^T \mathcal{E} \mathcal{W}$ ,  $\hat{\mathcal{A}} = \mathcal{W}^T \mathcal{A} \mathcal{W} \in \mathbb{C}^{r \times r}$ ,  $\hat{\mathcal{B}} = \mathcal{W}^T \mathcal{B} \in \mathbb{C}^{r \times m}$ ,  $\hat{\mathcal{C}} = \mathcal{C} \mathcal{W} \in \mathbb{C}^{p \times r}$ .

- It seems as if no  $\ell$ th order ODE can be extracted.

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# Approach 1

[Freund 2005]

The matrices  $\mathcal{M}_F$  and  $\mathcal{R}_F$  have a particular structure

$$\mathcal{M}_F = (s_0 \mathcal{E}_F + \mathcal{A}_F)^{-1} \mathcal{E}_F = (\mathbf{c} \otimes I_n) \begin{bmatrix} M^{(1)} & M^{(2)} & M^{(3)} & \dots & M^{(\ell)} \end{bmatrix} + \Sigma \otimes I_n,$$

$$\mathcal{R}_F = (s_0 \mathcal{E}_F + \mathcal{A}_F)^{-1} \mathcal{B}_F = \mathbf{c} \otimes R,$$

where

$$M^{(i)} = (P(s_0))^{-1} \sum_{j=0}^{\ell-i} s_0^j P_{i+j} \in \mathbb{C}^{n \times n}, i = 1, \dots, \ell$$

$$R = (P(s_0))^{-1} B \in \mathbb{C}^{n \times m},$$

$$\mathbf{c} = \begin{bmatrix} 1 \\ s_0 \\ s_0^2 \\ \vdots \\ s_0^{\ell-1} \end{bmatrix}, \quad \Sigma = \begin{bmatrix} 0 & 0 & \dots & \dots & 0 \\ 1 & 0 & \ddots & & \vdots \\ s_0 & 1 & 0 & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ s_0^{\ell-2} & \dots & s_0 & 1 & 0 \end{bmatrix} \in \mathbb{C}^{\ell \times \ell}.$$



# Approach 1

[Freund 2005]

## Theorem (Freund 2005)

Let  $\mathcal{M}_F = (c \otimes I_n) \begin{bmatrix} M^{(1)} & M^{(2)} & M^{(3)} & \dots & M^{(\ell)} \end{bmatrix} + \Sigma \otimes I_n$ , and  $\mathcal{R}_F = c \otimes R$  with  $c \in \mathbb{C}^\ell$ ,  $c_j \neq 0, j = 1, \dots, \ell$ ,  $R \in \mathbb{C}^{n \times m}$ ,  $M^{(i)} \in \mathbb{C}^{n \times n}, i = 1, \dots, \ell$ ,  $\Sigma \in \mathbb{C}^{\ell \times \ell}$ . Let  $\mathcal{W} \in \mathbb{C}^{\ell n \times r}$  be any basis of the block-Krylov subspace  $\mathcal{K}_s(\mathcal{M}_F, \mathcal{R}_F), r \leq sm$ . Then  $\mathcal{W}$  can be represented in the form

$$\begin{bmatrix} WU^{(1)} \\ WU^{(2)} \\ \vdots \\ WU^{(\ell)} \end{bmatrix} \quad \text{where } W \in \mathbb{C}^{n \times r} \text{ and, for each } i = 1, 2, \dots, \ell, \\ U^{(i)} \in \mathbb{C}^{r \times r} \text{ is nonsingular and upper triangular.}$$

- $\mathcal{K}_s(\mathcal{M}_F, \mathcal{R}_F) \subset \mathbb{C}^{\ell n}$  consists of  $\ell$  'copies' of the subspace  $S_r = \text{span}\{W\} \subset \mathbb{C}^n$ .
- Let  $V$  be the matrix representing an orthonormal basis of  $\text{span}\{W\}$ .
- Choose

$$\mathcal{V} = \text{diag}(V, V, \dots, V) \in \mathbb{C}^{\ell n \times \ell r}, \mathcal{V}^H \mathcal{V} = I_r.$$

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# Approach 1

[Freund 2005]

- Project the first order system using  $\mathcal{V}$

$$(\mathcal{V}^H \mathcal{E}_F \mathcal{V}) \mathcal{V}^H \frac{d}{dt} z(t) + (\mathcal{V}^H \mathcal{A}_F \mathcal{V}) \mathcal{V}^H z(t) = (\mathcal{V}^H \mathcal{B}_F) u(t)$$

$$y(t) = \mathcal{D}_F u(t) + (\mathcal{C}_F \mathcal{V}) \mathcal{V}^H z(t)$$

with

$$\mathcal{V}^H \mathcal{B}_F = \begin{bmatrix} 0 \\ \vdots \\ 0 \\ \mathcal{V}^H B \end{bmatrix}, \quad \mathcal{V}^H \mathcal{A}_F \mathcal{V} = \begin{bmatrix} 0 & -I_n & 0 & \cdots & 0 \\ 0 & 0 & -I_n & \ddots & \vdots \\ \vdots & \ddots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & 0 & -I_n \\ \mathcal{V} P_0 \mathcal{V}^H & \mathcal{V} P_1 \mathcal{V}^H & \mathcal{V} P_2 \mathcal{V}^H & \cdots & \mathcal{V} P_{\ell-1} \mathcal{V}^H \end{bmatrix},$$

$$\mathcal{V}^H \mathcal{E}_F \mathcal{V} = \begin{bmatrix} I_{(\ell-1)n} & \\ & \mathcal{V}^H P_\ell \mathcal{V} \end{bmatrix}, \quad \mathcal{C}_F \mathcal{V} = [C_0 \mathcal{V} \quad C_1 \mathcal{V} \quad \cdots \quad C_{\ell-1} \mathcal{V}], \quad \mathcal{D}_F = D.$$

- An  $\ell$ th order reduced order system can be read off immediately.
- The first moments of the reduced order system match those of the original system.

# Approach 1

[Freund 2005]

- Project the first order system using  $\mathcal{V}$

$$(\mathcal{V}^H \mathcal{E}_F \mathcal{V}) \mathcal{V}^H \frac{d}{dt} z(t) + (\mathcal{V}^H \mathcal{A}_F \mathcal{V}) \mathcal{V}^H z(t) = (\mathcal{V}^H \mathcal{B}_F) u(t)$$

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- An  $\ell$ th order reduced order system can be read off immediately.
- The first moments of the reduced order system match those of the original system.

# Approach 1

[Freund 2005]

- Project the first order system using  $\mathcal{V}$

$$(\mathcal{V}^H \mathcal{E}_F \mathcal{V}) \mathcal{V}^H \frac{d}{dt} z(t) + (\mathcal{V}^H \mathcal{A}_F \mathcal{V}) \mathcal{V}^H z(t) = (\mathcal{V}^H \mathcal{B}_F) u(t)$$

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- An  $\ell$ th order reduced order system can be read off immediately.
- The first moments of the reduced order system match those of the original system.



## Approach 1 and 2

- Approach 1 and 2 use companion form linearization.
- Approach 1 uses block-Krylov subspace  $\mathcal{K}_s(\mathcal{M}_F, \mathcal{R}_F)$  with  $\mathcal{M}_F = (s_0 \mathcal{E}_F + \mathcal{A}_F)^{-1} \mathcal{E}_F$  and  $\mathcal{R}_F = (s_0 \mathcal{E}_F + \mathcal{A}_F)^{-1} \mathcal{B}_F$ .
- Approach 2 uses block-Krylov subspace  $\mathcal{K}_s(\mathcal{M}_B, \mathcal{R}_B)$  with  $\mathcal{M}_B = \mathcal{A}_B^{-1} \mathcal{E}_B$  and  $\mathcal{R}_B = \mathcal{A}_B^{-1} \mathcal{B}_B$ .
- Neither  $\lambda \mathcal{E}_F + \mathcal{A}_F$  nor  $\lambda \mathcal{E}_B + \mathcal{A}_B$  is structure-preserving, e.g.,  $(-\lambda \mathcal{E}_F + \mathcal{A}_F)^T \neq \lambda \mathcal{E}_F + \mathcal{A}_F$  and  $(-\lambda \mathcal{E}_B + \mathcal{A}_B)^T \neq \lambda \mathcal{E}_B + \mathcal{A}_B$ .
- There are numerous other linearizations.

# Approach 1 and 2

- Approach 1 and 2 use companion form linearization.
- Approach 1 uses block-Krylov subspace  $\mathcal{K}_s(\mathcal{M}_F, \mathcal{R}_F)$  with  $\mathcal{M}_F = (\mathbf{s}_0 \mathcal{E}_F + \mathcal{A}_F)^{-1} \mathcal{E}_F$  and  $\mathcal{R}_F = (\mathbf{s}_0 \mathcal{E}_F + \mathcal{A}_F)^{-1} \mathcal{B}_F$ .
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## Vector space $\mathbb{L}_1(P)$ of linearizations – Motivation

Systematic way to construct linearizations that allow for the preservation of structure and/or are better conditioned than the companion forms.

[Mackey, Mackey, Mehl, Mehrmann, SIMAX 2006] = [4M]

$$P(\lambda)x = \sum_{i=0}^{\ell} \lambda^i P_i x$$

$\Rightarrow$  linearization of size  $\ell n \times \ell n$

$$\underbrace{\left( \lambda \begin{bmatrix} P_{\ell} & 0 & 0 & \cdots & 0 \\ 0 & I_n & 0 & \cdots & 0 \\ 0 & 0 & I_n & \cdots & 0 \\ \vdots & \vdots & \ddots & \ddots & \vdots \\ 0 & 0 & \cdots & 0 & I_n \end{bmatrix} + \begin{bmatrix} P_{\ell-1} & P_{\ell-2} & \cdots & P_1 & P_0 \\ -I_n & 0 & \cdots & 0 & 0 \\ 0 & -I_n & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & -I_n & 0 \end{bmatrix} \right)}_{\mathcal{L}_1(\lambda)} \begin{bmatrix} \lambda^{\ell-1} x \\ \lambda^{\ell-2} x \\ \vdots \\ \lambda x \\ x \end{bmatrix} = \begin{bmatrix} P(\lambda)x \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

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# Matrix Polynomials – (Strong) Linearization

## Definition (Linearization)

A pencil  $\mathcal{L}(\lambda) = \lambda \mathcal{E} + \mathcal{A}$  with  $\mathcal{E}, \mathcal{A} \in \mathbb{R}^{kn \times kn}$  is called a **linearization** of  $P(\lambda) \in \Pi_\ell^n$  if there exist unimodular matrix polynomials  $E(\lambda), F(\lambda)$  such that

$$E(\lambda)\mathcal{L}(\lambda)F(\lambda) = \left[ \begin{array}{c|c} P(\lambda) & 0 \\ \hline 0 & I_{(k-1)n} \end{array} \right]$$

for some  $k \in \mathbb{N}$ . A matrix polynomial  $E(\lambda)$  is **unimodular** if  $\det E(\lambda)$  is a nonzero constant.

## Theorem

[Lancaster, Psarrakos Report 2005]

For regular polynomials  $P(\lambda)$  :

- any linearization: the Jordan structure of all finite eigenvalues is preserved.
- strong linearization: the Jordan structure of the eigenvalue  $\infty$  is preserved.

## Example

$$\lambda P_1 + P_0 = \lambda \begin{bmatrix} 4 & 5 \\ 0 & 0 \end{bmatrix} - \begin{bmatrix} 1 & 2 \\ 0 & 3 \end{bmatrix} \implies \lambda_1 = \frac{1}{4}, \lambda_2 = \frac{3}{0} = \infty.$$

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## Vector space $\mathbb{L}_1(P)$ of linearizations and Approach 1

- Freund considers

$$\mathcal{E}_F \frac{d}{dt} z(t) + \mathcal{A}_F z(t) = \mathcal{B}_F u(t)$$

$$y(t) = \mathcal{D}_F u(t) + \mathcal{C}_F z(t).$$

- Interpret Freund's approach in terms of the first companion form  $\mathcal{L}_1(\lambda) = \lambda \mathcal{E}_1 + \mathcal{A}_1$

$$\mathcal{E}_1 \frac{d}{dt} \tilde{z}(t) + \mathcal{A}_1 \tilde{z}(t) = \mathcal{B}_1 u(t)$$

$$y(t) = \mathcal{D}_F u(t) + \mathcal{C}_1 \tilde{z}(t).$$

with

$$\tilde{z}(t) = \mathcal{P}^T \tilde{z}(t)$$

$$\mathcal{B}_1 = \mathcal{P}^T \mathcal{B}$$

$$\mathcal{C}_1 = \mathcal{C}_F \mathcal{P}$$

as  $\mathcal{L}_1(\lambda) = \lambda \mathcal{E}_1 + \mathcal{A}_1 = \lambda \mathcal{P}^T \mathcal{E}_F \mathcal{P} + \mathcal{P}^T \mathcal{A}_F \mathcal{P}$  with  $\mathcal{P} = \begin{bmatrix} & & I_n \\ & \ddots & \\ I_n & & \end{bmatrix}$ .

## Vector space $\mathbb{L}_1(P)$ of linearizations and Approach 1

- Freund considers

$$\mathcal{E}_F \frac{d}{dt} z(t) + \mathcal{A}_F z(t) = \mathcal{B}_F u(t)$$

$$y(t) = \mathcal{D}_F u(t) + \mathcal{C}_F z(t).$$

- Interpret Freund's approach in terms of the first companion form  $\mathcal{L}_1(\lambda) = \lambda \mathcal{E}_1 + \mathcal{A}_1$

$$\mathcal{E}_1 \frac{d}{dt} \tilde{z}(t) + \mathcal{A}_1 \tilde{z}(t) = \mathcal{B}_1 u(t)$$

$$y(t) = \mathcal{D}_F u(t) + \mathcal{C}_1 \tilde{z}(t).$$

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$$\tilde{z}(t) = \mathcal{P}^T \tilde{z}(t)$$

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## Vector space $\mathbb{L}_1(P)$ of linearizations and Approach 1

- Approach is based on the Krylov subspace induced by  $\mathcal{M} = (\mathcal{L}_1(s_0))^{-1} \mathcal{E}_1$  and  $\mathcal{R} = (\mathcal{L}_1(s_0))^{-1} \mathcal{B}_1$ .

- All linearizations in  $\mathbb{L}_1$  can be written as

$$\mathcal{L}(\lambda) = [v \otimes I_n \quad W] \mathcal{L}_1(\lambda) = \mathcal{T} \mathcal{L}_1(\lambda) = \lambda \mathcal{T} \mathcal{E}_1 + \mathcal{T} \mathcal{A}_1$$

with  $v \in \mathbb{R}^\ell$ ,  $W \in \mathbb{R}^{\ell n \times (\ell-1)n}$  such that  $\mathcal{T} = [v \otimes I_n \quad W]$  is nonsingular.

- As

$$(\mathcal{T} \mathcal{E}_1) \frac{d}{dt} z(t) + (\mathcal{T} \mathcal{A}_1) z(t) = (\mathcal{T} \mathcal{B}_1) u(t)$$

and

$$(\mathcal{L}(s_0))^{-1} (\mathcal{T} \mathcal{E}_1) = (\mathcal{L}_1(s_0))^{-1} \mathcal{E}_1 = \mathcal{M},$$

$$(\mathcal{L}(s_0))^{-1} (\mathcal{T} \mathcal{B}_1) = (\mathcal{L}_1(s_0))^{-1} \mathcal{B}_1 = \mathcal{R},$$

all linearization in  $\mathbb{L}_1$  will yield (theoretically) the same reduced order system.

- A similar observation holds for Approach 2.



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## Vector space $\mathbb{L}_1(P)$ – Structured Linearizations

Gyroscopic system  $P(\lambda) = P(-\lambda)^T \in \Pi_2^n$

$$P(\lambda) = \lambda^2 M + \lambda G + K, \quad M = M^T, G = -G^T, K = K^T, \quad M, G, K \in \mathbb{R}^{n \times n}.$$

Companion form in  $\mathbb{L}_1(P)$

$$\mathcal{L}_1(\lambda) = \begin{bmatrix} M & 0 \\ 0 & I \end{bmatrix} + \begin{bmatrix} G & K \\ -I & 0 \end{bmatrix}$$

is not structure preserving as  $\mathcal{L}_1(\lambda) \neq \mathcal{L}_1(-\lambda)^T$ .

Structured linearization in  $\mathbb{L}_1(P)$

$$\mathcal{L}(\lambda) = \lambda \begin{bmatrix} 0 & -M \\ M & G \end{bmatrix} + \begin{bmatrix} M & 0 \\ 0 & K \end{bmatrix} \in \mathbb{L}_1(P)$$

is a structure-preserving linearization ( $\mathcal{L}(\lambda) = \mathcal{L}(-\lambda)^T$ ).

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## Vector space $\mathbb{L}_1(P)$ – Structured Linearizations

Robot  $P(\lambda) = P(-\lambda)^T \in \Pi_4^n$

$$P(\lambda) = \lambda^4 P_4 + \lambda^3 P_3 + \lambda^2 P_2 + \lambda P_1 + P_0, \quad P_i = (-1)^i P_i^T, \quad P_i \in \mathbb{R}^{n \times n}, i = 0, \dots, 4.$$

Companion form in  $\mathbb{L}_1(P)$

$$\mathcal{L}_1(\lambda) = \lambda \begin{bmatrix} P_4 & 0 & 0 & 0 \\ 0 & I_n & 0 & 0 \\ 0 & 0 & I_n & 0 \\ 0 & 0 & 0 & I_n \end{bmatrix} + \begin{bmatrix} P_3 & P_2 & P_1 & P_0 \\ -I_n & 0 & 0 & 0 \\ 0 & -I_n & 0 & 0 \\ 0 & 0 & -I_n & 0 \end{bmatrix}$$

Structured linearizations in  $\mathbb{L}_1(P)$

different [4M]

$$\mathcal{L}(\lambda) = \lambda \begin{bmatrix} 0 & -P_4 & 0 & -P_4 \\ P_4 & P_3 & P_4 & P_3 \\ 0 & -P_4 & P_1 - P_3 & P_0 - P_2 \\ P_4 & P_3 & P_2 - P_0 & P_1 \end{bmatrix} + \begin{bmatrix} P_4 & 0 & P_4 & 0 \\ 0 & P_2 - P_4 & P_1 - P_3 & P_0 \\ P_4 & P_3 - P_1 & P_2 - P_0 & 0 \\ 0 & P_0 & 0 & P_0 \end{bmatrix}$$

# Vector space $\mathbb{L}_1(P)$ – Structured Linearizations

Robot  $P(\lambda) = P(-\lambda)^T \in \Pi_4^n$

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Structured linearizations in  $\mathbb{L}_1(P)$

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$$\mathcal{L}(\lambda) = \lambda \begin{bmatrix} 0 & -P_4 & 0 & -P_4 \\ P_4 & P_3 & P_4 & P_3 \\ 0 & -P_4 & P_1 - P_3 & P_0 - P_2 \\ P_4 & P_3 & P_2 - P_0 & P_1 \end{bmatrix} + \begin{bmatrix} P_4 & 0 & P_4 & 0 \\ 0 & P_2 - P_4 & P_1 - P_3 & P_0 \\ P_4 & P_3 - P_1 & P_2 - P_0 & 0 \\ 0 & P_0 & 0 & P_0 \end{bmatrix}$$



## Vector space $\mathbb{L}_1(P)$ – Structured Linearizations

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Companion form in  $\mathbb{L}_1(P)$

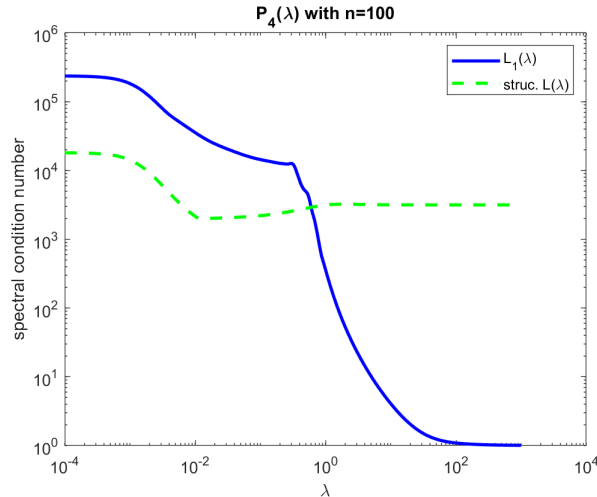
$$\mathcal{L}_1(\lambda) = \lambda \begin{bmatrix} P_4 & 0 & 0 & 0 \\ 0 & I_n & 0 & 0 \\ 0 & 0 & I_n & 0 \\ 0 & 0 & 0 & I_n \end{bmatrix} + \begin{bmatrix} P_3 & P_2 & P_1 & P_0 \\ -I_n & 0 & 0 & 0 \\ 0 & -I_n & 0 & 0 \\ 0 & 0 & -I_n & 0 \end{bmatrix}$$

Structured linearizations in  $\mathbb{L}_1(P)$

different [4M]

$$\mathcal{L}(\lambda) = \lambda \begin{bmatrix} 0 & -P_4 & 0 & -P_4 \\ P_4 & P_3 & P_4 & P_3 \\ 0 & -P_4 & P_1 - P_3 & P_0 - P_2 \\ P_4 & P_3 & P_2 - P_0 & P_1 \end{bmatrix} + \begin{bmatrix} P_4 & 0 & P_4 & 0 \\ 0 & P_2 - P_4 & P_1 - P_3 & P_0 \\ P_4 & P_3 - P_1 & P_2 - P_0 & 0 \\ 0 & P_0 & 0 & P_0 \end{bmatrix}$$

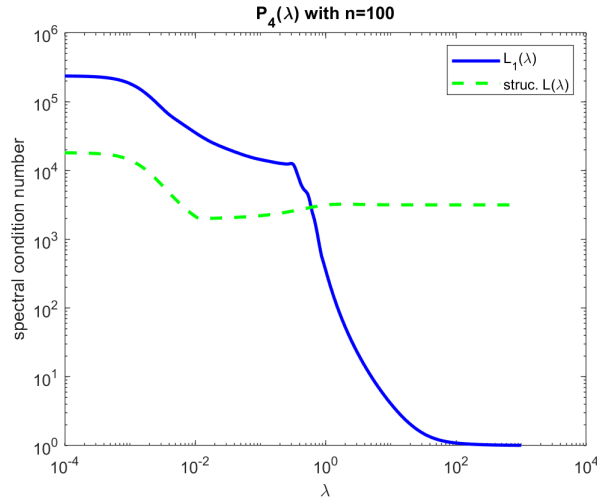
# Vector space $\mathbb{L}_1(P)$ – Structured Linearizations



$\mathcal{L}_1(\lambda)$  and  $\mathcal{L}(\lambda)$  may be very differently conditioned.

```
P0=1/100*gallery('poisson',10);  
P2=randn(100);P2=(P2+P2')/30;  
P4=eye(n);  
P1=rand(100);P1=P1-P1';  
P3=randn(100);P3=P3-P3';
```

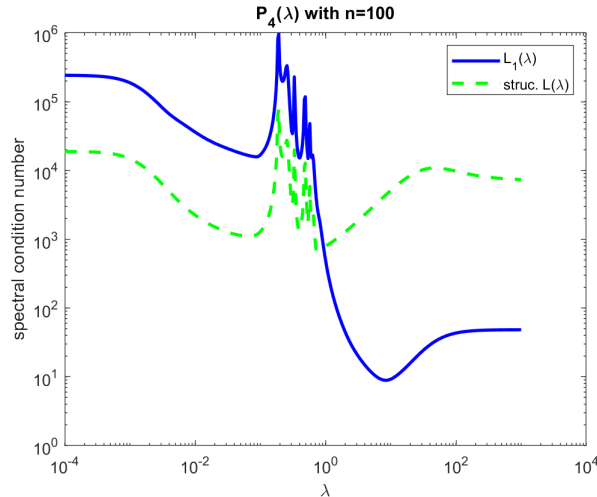
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# Vector space $\mathbb{L}_1(P)$ – Structured Linearizations

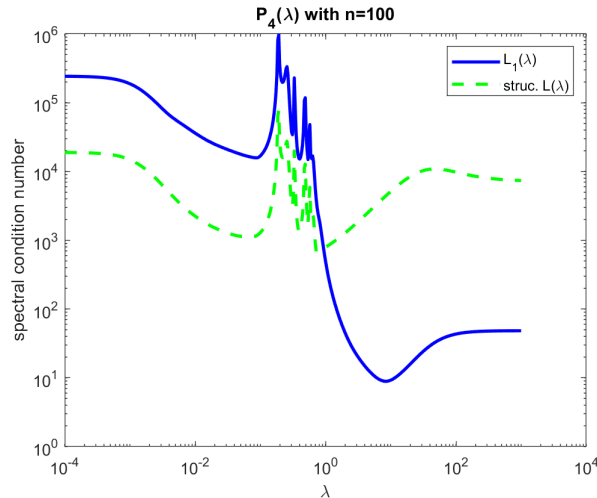


$\mathcal{L}_1(\lambda)$  and  $\mathcal{L}(\lambda)$  may be very differently conditioned.

$\mathcal{L}(\lambda)$  is not (block) sparse, while  $\mathcal{L}_1(\lambda)$  is.

```
P0=1/100*gallery('poisson',10);  
P2=randn(100);P2=(P2+P2')/5;  
P4=.5*gallery('poisson',10);  
P1=rand(100);P1=P1-P1';  
P3=randn(100);P3=P3-P3';
```

# Vector space $\mathbb{L}_1(P)$ – Structured Linearizations



$\mathcal{L}_1(\lambda)$  and  $\mathcal{L}(\lambda)$  may be very differently conditioned.  
 $\mathcal{L}(\lambda)$  is not (block) sparse, while  $\mathcal{L}_1(\lambda)$  is.

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P1=rand(100);P1=P1-P1';  
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```

# Structured Linearization not in $\mathbb{L}_1(P)$

Robot  $P(\lambda) = P(-\lambda)^T \in \Pi_4^n$

$$P(\lambda) = \lambda^4 P_4 + \lambda^3 P_3 + \lambda^2 P_2 + \lambda P_1 + P_0, \quad P_i = (-1)^i P_i^T, \quad P_i \in \mathbb{R}^{n \times n}, i = 0, \dots, 4.$$

(Structured) Linearization not in  $\mathbb{L}_1(P)$

$$\mathcal{L}(\lambda) = \left[ \begin{array}{ccc|cc} P_4 & 0 & 0 & I & 0 \\ 0 & -P_2 - \lambda P_3 & 0 & \lambda I & I \\ 0 & 0 & P_0 + \lambda P_1 & 0 & \lambda I \\ \hline I & -\lambda I & 0 & 0 & 0 \\ 0 & I & -\lambda I & 0 & 0 \end{array} \right] = \lambda \mathcal{E} + \mathcal{A} \quad \text{Note: } \mathcal{E}, \mathcal{A} \in \mathbb{R}^{5n \times 5n}$$

as

$$\mathcal{V}(\lambda) \mathcal{L}(\lambda) \mathcal{U}(\lambda) = \text{diag}(I_{4n}, P(\lambda))$$

for

$$\mathcal{V}(\lambda) = \left[ \begin{array}{ccccc} I_n & 0 & 0 & -P_4 & -\lambda P_4 \\ -\lambda I_n & I_n & 0 & \lambda P_4 & \lambda^2 P_4 + \lambda P_3 + P_2 \\ 0 & 0 & 0 & I_n & 0 \\ 0 & 0 & 0 & 0 & I_n \\ \lambda^2 I_n & -\lambda I_n & I_n & -\lambda^2 P_4 & -\lambda^3 P_4 - \lambda^2 P_3 - \lambda P_2 \end{array} \right], \quad \mathcal{U}(\lambda) = \left[ \begin{array}{ccccc} 0 & 0 & I_n & \lambda I_n & \lambda^2 I_n \\ 0 & 0 & 0 & I_n & \lambda I_n \\ 0 & 0 & 0 & 0 & I_n \\ I_n & 0 & 0 & 0 & -\lambda^2 P_4 \\ 0 & I_n & 0 & 0 & \lambda^3 P_4 + \lambda^2 P_3 + \lambda P_2 \end{array} \right].$$

$$\det \mathcal{U}(\lambda) = \det \mathcal{V}(\lambda) = 1.$$

## Structured Linearization not in $\mathbb{L}_1(P)$

Robot  $P(\lambda) = P(-\lambda)^T \in \Pi_4^n$

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(Structured) Linearization not in  $\mathbb{L}_1(P)$

$$\mathcal{L}(\lambda) = \left[ \begin{array}{ccc|cc} P_4 & 0 & 0 & I & 0 \\ 0 & -P_2 - \lambda P_3 & 0 & \lambda I & I \\ 0 & 0 & P_0 + \lambda P_1 & 0 & \lambda I \\ \hline I & -\lambda I & 0 & 0 & 0 \\ 0 & I & -\lambda I & 0 & 0 \end{array} \right] = \lambda \mathcal{E} + \mathcal{A} \quad \text{Note } \mathcal{E}, \mathcal{A} \in \mathbb{R}^{5n \times 5n!}$$

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$$\mathcal{V}(\lambda) = \begin{bmatrix} I_n & 0 & 0 & -P_4 & -\lambda P_4 \\ -\lambda I_n & I_n & 0 & \lambda P_4 & \lambda^2 P_4 + \lambda P_3 + P_2 \\ 0 & 0 & 0 & I_n & 0 \\ 0 & 0 & 0 & 0 & I_n \\ \lambda^2 I_n & -\lambda I_n & I_n & -\lambda^2 P_4 & -\lambda^3 P_4 - \lambda^2 P_3 - \lambda P_2 \end{bmatrix}, \quad \mathcal{U}(\lambda) = \begin{bmatrix} 0 & 0 & I_n & \lambda I_n & \lambda^2 I_n \\ 0 & 0 & 0 & I_n & \lambda I_n \\ 0 & 0 & 0 & 0 & I_n \\ I_n & 0 & 0 & 0 & -\lambda^2 P_4 \\ 0 & I_n & 0 & 0 & \lambda^3 P_4 + \lambda^2 P_3 + \lambda P_2 \end{bmatrix}.$$

$$\det \mathcal{U}(\lambda) = \det \mathcal{V}(\lambda) = 1.$$



# Block Kronecker Ansatz space $\mathbb{G}_{r+1}$

## Definition [Block Kronecker Ansatz space]

[FS-2]

Let  $P(\lambda) \in \Pi_\ell^n$  with  $\ell = r + s + 1$ . The **block Kronecker ansatz space**  $\mathbb{G}_{r+1}(P)$  is the set of all  $\ell n \times \ell n$  matrix pencils  $\mathbb{L}(\lambda)$  that satisfy the block Kronecker ansatz equation

$$\left[ \begin{array}{c|c} [\lambda^r I_n \ \cdots \ I_n] & \\ \hline & I_{sn} \end{array} \right] \overbrace{\left[ \begin{array}{c|c} \mathcal{L}_{11}(\lambda) & \mathcal{L}_{12}(\lambda) \\ \hline \mathcal{L}_{21}(\lambda) & \mathcal{L}_{22}(\lambda) \end{array} \right]}^{\mathcal{L}(\lambda)} \left[ \begin{array}{c|c} \begin{bmatrix} \lambda^s I_n \\ \vdots \\ I_n \end{bmatrix} & \\ \hline & I_{rn} \end{array} \right] = \left[ \begin{array}{c|c} \alpha P(\lambda) & 0 \\ \hline 0 & 0 \end{array} \right].$$

- $\mathbb{G}_{r+1}(P)$  is a vector space over  $\mathbb{R}$  of dimension  $(\ell - 1)\ell n^2 + 1$ . [FS-2]
- Thus,  $\mathbb{L}_1(P) \neq \mathbb{G}_{r+1}(P)$ .
- Almost all pencils in  $\mathbb{G}_{r+1}(P)$  are strong linearizations of  $P(\lambda)$ . [FS-2]

# Block Kronecker Ansatz space $\mathbb{G}_{r+1}$

## Definition [Block Kronecker Ansatz space]

[FS-2]

Let  $P(\lambda) \in \Pi_\ell^n$  with  $\ell = r + s + 1$ . The **block Kronecker ansatz space**  $\mathbb{G}_{r+1}(P)$  is the set of all  $\ell n \times \ell n$  matrix pencils  $\mathbb{L}(\lambda)$  that satisfy the block Kronecker ansatz equation

$$\left[ \begin{array}{c|c} [\lambda^r I_n \ \cdots \ I_n] & \\ \hline & I_{sn} \end{array} \right] \overbrace{\left[ \begin{array}{c|c} \mathcal{L}_{11}(\lambda) & \mathcal{L}_{12}(\lambda) \\ \hline \mathcal{L}_{21}(\lambda) & \mathcal{L}_{22}(\lambda) \end{array} \right]}^{\mathcal{L}(\lambda)} \left[ \begin{array}{c|c} \begin{bmatrix} \lambda^s I_n \\ \vdots \\ I_n \end{bmatrix} & \\ \hline & I_{rn} \end{array} \right] = \left[ \begin{array}{c|c} \alpha P(\lambda) & 0 \\ \hline 0 & 0 \end{array} \right].$$

- $\mathbb{G}_{r+1}(P)$  is a vector space over  $\mathbb{R}$  of dimension  $(\ell - 1)\ell n^2 + 1$ . [FS-2]
- Thus,  $\mathbb{L}_1(P) \neq \mathbb{G}_{r+1}(P)$ .
- Almost all pencils in  $\mathbb{G}_{r+1}(P)$  are strong linearizations of  $P(\lambda)$ . [FS-2]

# Block Kronecker Ansatz space $\mathbb{G}_{r+1}$

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# Higher order system and block Kronecker linearizations

Robot  $P(\lambda) \in \Pi_4^n$

$$P_4 \frac{d^4}{dt^4} x(t) + P_3 \frac{d^3}{dt^3} x(t) + P_2 \frac{d^2}{dt^2} x(t) + P_1 \frac{d}{dt} x(t) + P_0 x(t) = Bu(t)$$

$$Du(t) + C_3 \frac{d^3}{dt^3} x(t) + C_2 \frac{d^2}{dt^2} x(t) + C_1 \frac{d}{dt} x(t) + C_0 x(t) = y(t)$$

The linearization

$$\mathcal{L}(\lambda) = \lambda \mathcal{E} + \mathcal{A} = \left[ \begin{array}{ccc|cc} P_4 & 0 & 0 & I & 0 \\ 0 & -P_2 - \lambda P_3 & 0 & \lambda I & I \\ 0 & 0 & P_0 + \lambda P_1 & 0 & \lambda I \\ \hline I & -\lambda I & 0 & 0 & 0 \\ 0 & I & -\lambda I & 0 & 0 \end{array} \right]$$

does not give an equivalent first order ODE of the form  $\mathcal{E} \frac{d}{dt} z(t) + \mathcal{A} z(t) = \mathcal{B} u(t)$

$$\text{as } \begin{bmatrix} \lambda^2 I_n & -\lambda I_n & I_n & 0 & 0 \end{bmatrix} \left[ \begin{array}{ccc|cc} P_4 & 0 & 0 & I & 0 \\ 0 & -P_2 - \lambda P_3 & 0 & \lambda I & I \\ 0 & 0 & P_0 + \lambda P_1 & 0 & \lambda I \\ \hline I & -\lambda I & 0 & 0 & 0 \\ 0 & I & -\lambda I & 0 & 0 \end{array} \right] \begin{bmatrix} \lambda^2 I_n \\ \lambda I_n \\ I_n \\ 0 \\ 0 \end{bmatrix} = P(\lambda).$$

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# Block Kronecker Ansatz space $\mathbb{G}_{r+1}$

In  $\mathbb{L}_1$  all linearizations are based on  $\mathcal{L}_1(\lambda)$ , the linearizations in  $\mathbb{G}_{r+1}$  are based on

$$\mathcal{L}_K(\lambda) = \lambda \mathcal{E}_K + \mathcal{A}_K$$

$$= \left[ \begin{array}{cccc|ccc} \lambda \alpha P_\ell + \alpha P_{\ell-1} & \alpha P_{\ell-2} & \cdots & \alpha P_r & -I_n & & \\ & & & \alpha P_{r-1} & \lambda I_n & \ddots & \\ & & & \vdots & & \ddots & -I_n \\ & & & \alpha P_0 & & & \lambda I_n \\ \hline & -I_n & & & & & \\ & & \lambda I_n & & & & \\ & & & \ddots & & & \\ & & & & -I_n & & \lambda I_n \\ & & & & & 0 & \end{array} \right]$$

$$= \begin{bmatrix} \Sigma_r(\lambda) & L_r^T(\lambda) \\ L_s(\lambda) & 0 \end{bmatrix}$$

with  $\ell = r + s + 1$ ,  $\Sigma_r(\lambda) \in \mathbb{C}^{(r+1)n \times sn}$ , and  $L_j(\lambda) \in \mathbb{C}^{jn \times (j+1)n}$ .



## Block Kronecker Ansatz space $\mathbb{G}_{r+1}$

- We can find  $\mathcal{B}_K, \mathcal{C}_K$  such that

$$G(s) = D + \sum_{j=0}^{\ell-1} \mathcal{C}_j((P(s))^{-1}B = \mathcal{D}_K + \mathcal{C}_K(\mathcal{L}_K(s))^{-1}\mathcal{B}_K.$$

- Introduce shift  $s_0 \in \mathbb{C}$  such that  $\mathcal{L}_K(s_0) = s_0\mathcal{E}_K + \mathcal{A}_K$  is nonsingular. Then

$$G(s) = \mathcal{D}_K + \mathcal{C}_K(\mathcal{L}_K(s))^{-1}\mathcal{B}_K = \mathcal{D}_K + \mathcal{C}_K(I + (s - s_0)\mathcal{M}_K)^{-1}\mathcal{R}_K$$

with

$$\mathcal{M}_K = (\mathcal{L}_K(s_0))^{-1}\mathcal{E}_K, \quad \mathcal{R}_K = (\mathcal{L}_K(s_0))^{-1}\mathcal{B}_K.$$

- Compute basis of  $\mathcal{K}_s(\mathcal{M}_K, \mathcal{R}_K)$ . Represent the basis in block form

$$\begin{bmatrix} W_1 \\ W_2 \\ \vdots \\ W_\ell \end{bmatrix}, \quad W_j \in \mathbb{C}^{n \times r}.$$

- Generate reduced order higher order system via projection with  $V$ , the matrix representing an orthonormal basis of  $\text{span}\{W_{r+1}\}$ .

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## Block Kronecker Ansatz space $\mathbb{G}_{r+1}$

- Any linearization in  $\mathbb{G}_{r+1}$  can be expressed as

$$\tilde{\mathcal{L}}_K(\lambda) = \mathcal{T}_1 \mathcal{L}_K(\lambda) \mathcal{T}_2 \quad \text{with} \quad \mathcal{T}_1 = \left[ \begin{array}{c|c} I_{(r+1)n} & B_1 \\ \hline 0 & C_1 \end{array} \right], \quad \mathcal{T}_2 = \left[ \begin{array}{c|c} I_{(s+1)n} & 0 \\ \hline B_2 & C_2 \end{array} \right]$$

and  $B_1 \in \mathbb{R}^{(r+1)n \times sn}$ ,  $B_2 \in \mathbb{R}^{r n \times (s+1)n}$ ,  $C_1 \in \mathbb{R}^{sn \times sn}$ ,  $C_2 \in \mathbb{R}^{r n \times r n}$ .

- $G(s) = \mathcal{D}_K + \tilde{\mathcal{C}}_K(\tilde{\mathcal{L}}_K(s))^{-1} \tilde{\mathcal{B}}_K$  with  $\tilde{\mathcal{C}}_K = \mathcal{C}_K \mathcal{T}_2$ ,  $\tilde{\mathcal{B}}_K = \mathcal{T}_1 \mathcal{B}_K$ .

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$$\tilde{\mathcal{L}}_K(\lambda) = \mathcal{T}_1 \mathcal{L}_K(\lambda) \mathcal{T}_2 \quad \text{with} \quad \mathcal{T}_1 = \left[ \begin{array}{c|c} I_{(r+1)n} & B_1 \\ \hline 0 & C_1 \end{array} \right], \quad \mathcal{T}_2 = \left[ \begin{array}{c|c} I_{(s+1)n} & 0 \\ \hline B_2 & C_2 \end{array} \right]$$

and  $B_1 \in \mathbb{R}^{(r+1)n \times sn}$ ,  $B_2 \in \mathbb{R}^{r n \times (s+1)n}$ ,  $C_1 \in \mathbb{R}^{sn \times sn}$ ,  $C_2 \in \mathbb{R}^{r n \times r n}$ .

- $G(s) = \mathcal{D}_K + \tilde{\mathcal{C}}_K(\tilde{\mathcal{L}}_K(s))^{-1} \tilde{\mathcal{B}}_K$  with  $\tilde{\mathcal{C}}_K = \mathcal{C}_K \mathcal{T}_2$ ,  $\tilde{\mathcal{B}}_K = \mathcal{T}_1 \mathcal{B}_K$ .

- $G(s) = \mathcal{D}_K + \tilde{\mathcal{C}}_K(I + (s - s_0)\tilde{\mathcal{M}}_K)^{-1} \tilde{\mathcal{R}}_K$  with

$$\begin{aligned} \tilde{\mathcal{M}}_K &= (\tilde{\mathcal{L}}_K(s_0))^{-1} \mathcal{T}_1 \mathcal{E}_K \mathcal{T}_2, & \tilde{\mathcal{R}}_K &= (\tilde{\mathcal{L}}_K(s_0))^{-1} \tilde{\mathcal{B}}_K, \\ &= \mathcal{T}_2^{-1} \mathcal{M}_K \mathcal{T}_2, & &= \mathcal{T}_2^{-1} \mathcal{R}_K. \end{aligned}$$

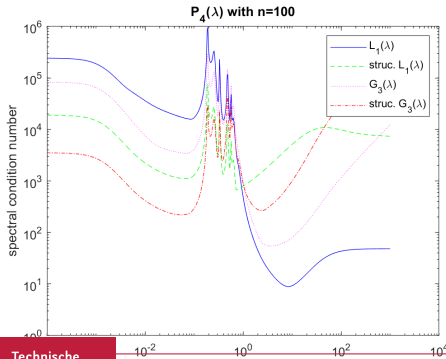
- Thus,  $\mathcal{K}(\tilde{\mathcal{M}}_K, \tilde{\mathcal{R}}_K) = \mathcal{T}_2^{-1} \mathcal{K}(\mathcal{M}_K, \mathcal{R}_K)$ .
- As before: Compute basis of  $\mathcal{K}_s(\tilde{\mathcal{M}}_K, \tilde{\mathcal{R}}_K)$ . Represent it in block form with blocks  $W_j \in \mathbb{C}^{n \times r}$ ,  $j = 1, \dots, \ell$ . Generate reduced order higher order system via projection with  $V$ , the matrix representing an orthonormal basis of  $\text{span}\{W_{r+1}\}$ .

# Four different Linearizations for Robot Example

Robot  $P(\lambda) \in \Pi_4^n$

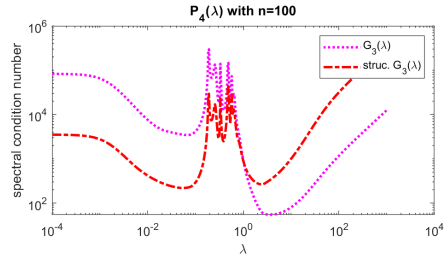
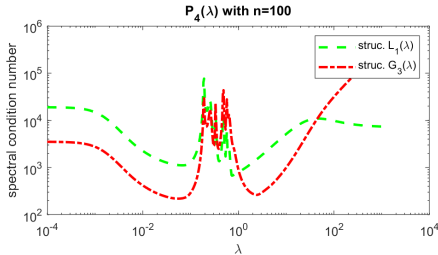
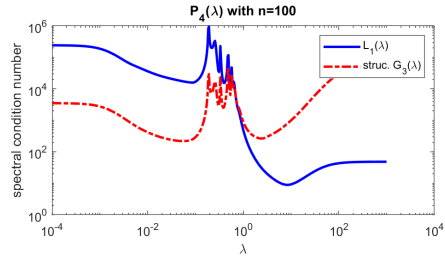
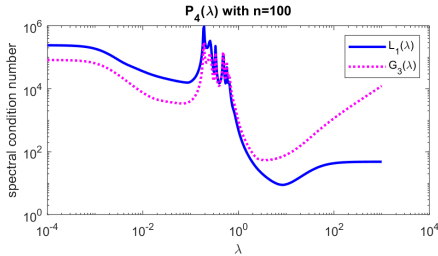
$$P_4 \frac{d^4}{dt^4} x(t) + P_3 \frac{d^3}{dt^3} x(t) + P_2 \frac{d^2}{dt^2} x(t) + P_1 \frac{d}{dt} x(t) + P_0 x(t) = Bu(t), \quad P_i = (-1)^i P_i^T$$

$$Du(t) + C_3 \frac{d^3}{dt^3} x(t) + C_2 \frac{d^2}{dt^2} x(t) + C_1 \frac{d}{dt} x(t) + C_0 x(t) = y(t)$$



```
P0=1/100*gallery('poisson',10);
P2=randn(100);P2=(P2+P2')/5;
P4=.5*gallery('poisson',10);
P1=rand(100);P1=P1-P1';
P3=randn(100);P3=P3-P3';
```

# Four different Linearizations for Robot Example

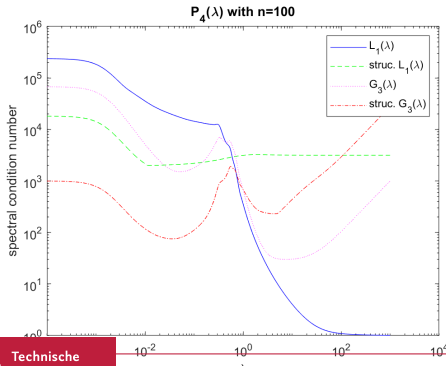


# Four different Linearizations for Robot Example

Robot  $P(\lambda) \in \Pi_4^n$

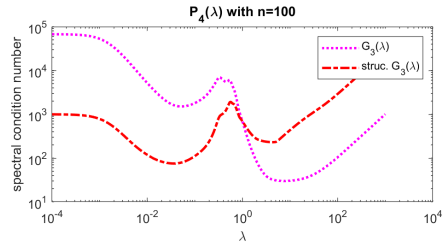
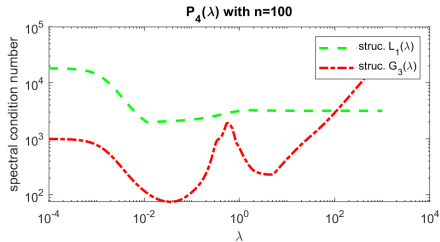
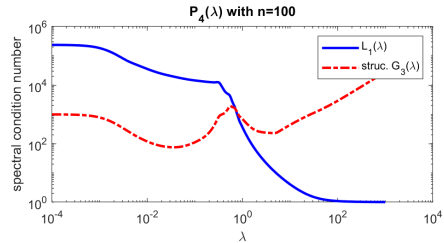
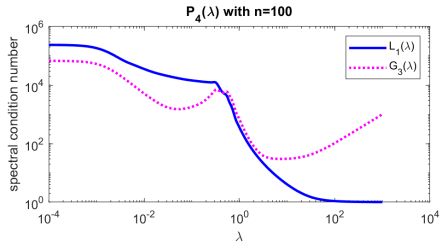
$$P_4 \frac{d^4}{dt^4} x(t) + P_3 \frac{d^3}{dt^3} x(t) + P_2 \frac{d^2}{dt^2} x(t) + P_1 \frac{d}{dt} x(t) + P_0 x(t) = Bu(t), \quad P_i = (-1)^i P_i^T$$

$$Du(t) + C_3 \frac{d^3}{dt^3} x(t) + C_2 \frac{d^2}{dt^2} x(t) + C_1 \frac{d}{dt} x(t) + C_0 x(t) = y(t)$$

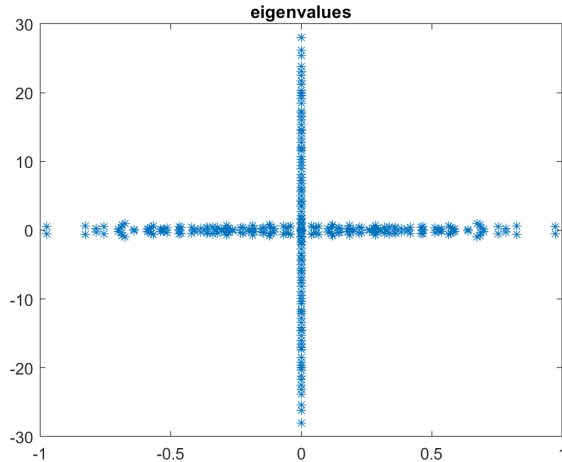


```
P0=1/100*gallery('poisson',10);
P2=randn(100);P2=(P2+P2')/30;
P4=eye(n);
P1=randn(100);P1=P1-P1';
P3=randn(100);P3=P3-P3';
```

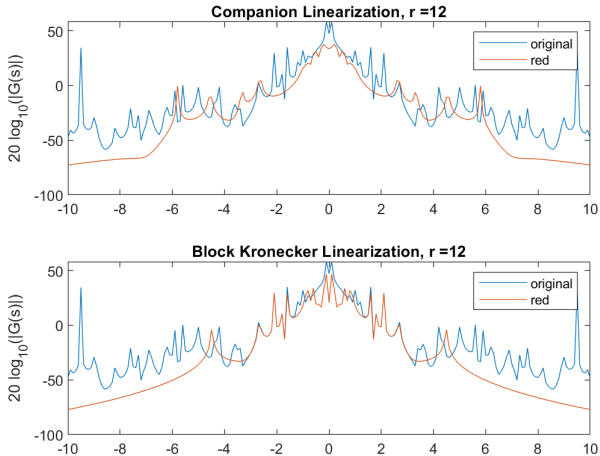
# Four different Linearizations for Robot Example



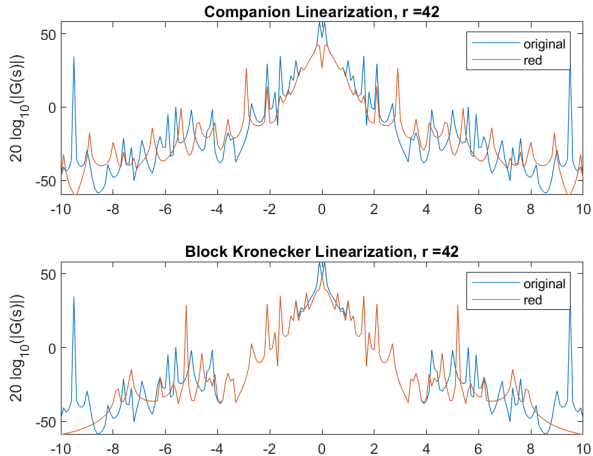
# Eigenvalues of Robot Example



# MOR for Robot Example, expansion points $\pm 0.5i$

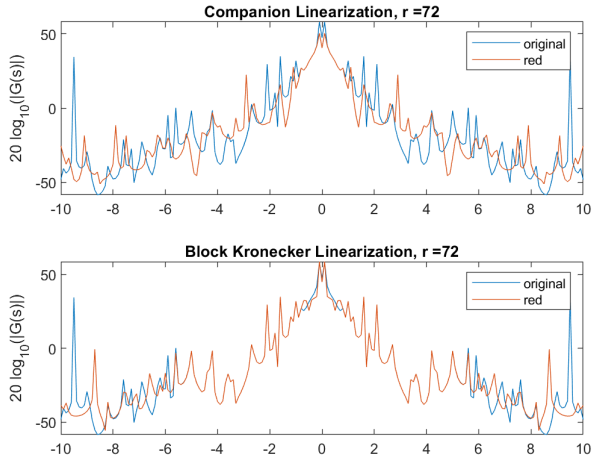


# MOR for Robot Example, expansion points $\pm 0.5\text{i}$





# MOR for Robot Example, expansion points $\pm 0.5\text{i}$



# Conclusions

- Galerkin projection based MOR for higher order LTI systems.
- Compute projection from linearization of higher order LTI system such that higher order system can be recovered.
- Vector spaces  $\mathbb{L}_1(P)$  and  $\mathbb{G}_{r+1}(P)$  allow to generate an abundance of linearizations.
- Linearizations have different condition.
  - It is not (yet) clear how to choose an optimally conditioned linearization.
  - For the structured robot example, the structured linearizations seem to be better conditioned.
- *LU* decomposition of linearization needs to be computed efficiently.
  - For block-dense linearizations, the LU decomposition can be computed in about  $\mathcal{O}(\ell^3 n^3)$  flops.
  - For the structured robot example, the LU decomposition of the structured block Kronecker linearization can be computed in just  $\mathcal{O}(n^3 + \ell^2 n^2)$  flops.
- Open question: What are the dominant poles of a higher order system?

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Some results from [FS-2] have been discovered independently in M. Bueno, F. Dopico, J. Pérez, R. Saavedra, B. Zykoski, *A unified approach to Fiedler-like pencils via strong block minimal bases pencils*. arXiv preprint, arXiv:1611.07170v1.

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