

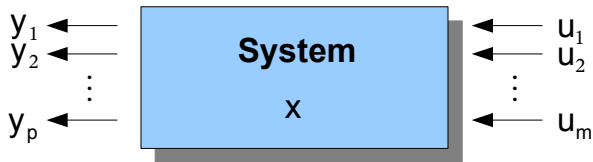
# Model Reduction Using Multi-level Substructuring

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- system completely determined by the mapping

$$G : u \mapsto y$$

# State space description

Linear time-invariant (LTI) dynamical system:

$$\begin{aligned} E\dot{x}(t) &= Ax(t) + Bu(t), & x(0) &= 0 \\ y(t) &= Cx(t) + Du(t), \end{aligned} \tag{1}$$

$A, E \in \mathbb{R}^{n \times n}$ ,  $B \in \mathbb{R}^{n \times m}$ ,  $C \in \mathbb{R}^{p \times n}$  and  $D \in \mathbb{R}^{p \times m}$

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- $u(t) \in \mathbb{R}^m$ ,  $y(t) \in \mathbb{R}^p \Rightarrow m$  inputs,  $p$  outputs
- $x(t) \in \mathbb{R}^n \Rightarrow n$  state space variables (order)
- abbreviation:

$$G = \left[ \begin{array}{c|c} sE - A & B \\ \hline C & D \end{array} \right]$$

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# Frequency domain

- Laplace transformation:  $u \mapsto U(s) := \int_0^{\infty} e^{-st} u(t) dt$

System output is obtained by simple multiplication:

$$Y = G \cdot U$$

- transfer function:

$$G(s) = C(sE - A)^{-1}B + D$$

Problem: state space dimension  $n$  is much too large



Replace system matrices

$$\left[ \begin{array}{c|c} sE - A & B \\ \hline C & D \end{array} \right] \longrightarrow \left[ \begin{array}{c|c} sE^{(k)} - A^{(k)} & B^{(k)} \\ \hline C^{(k)} & D \end{array} \right]$$



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- reduced order  $k$  is much smaller
- reproduce fundamental input/output behaviour, i.e.,  $G \approx G^{(k)}$
- preserve essential system properties
- w.l.o.g.  $D = 0$

- small-scale problems:
  - balancing methods (balanced truncation, stochastic balancing, positive real balancing, ...)
  - optimal Hankel norm approximation
  - proper orthogonal decomposition
- large-scale problems:
  - moment-matching methods (Arnoldi, Lanczos, Rational Krylov)
  - low-rank ADI iteration

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What if application not possible or inefficient?

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What if application not possible or inefficient?

## Remedy

Combine your favourite method with multi-level substructuring!

Strategy:

- 1 Decompose large system in many small decoupled ones
- 2 Reduce solely the small problems



Reduction methods are applicable!

## Strategy:

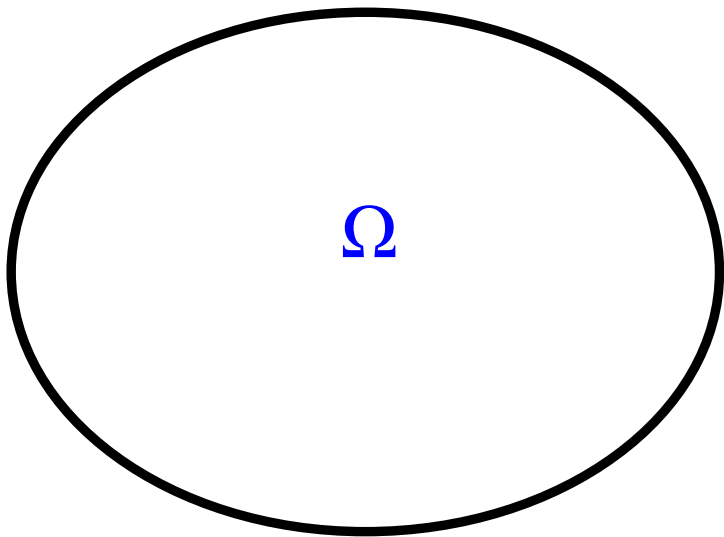
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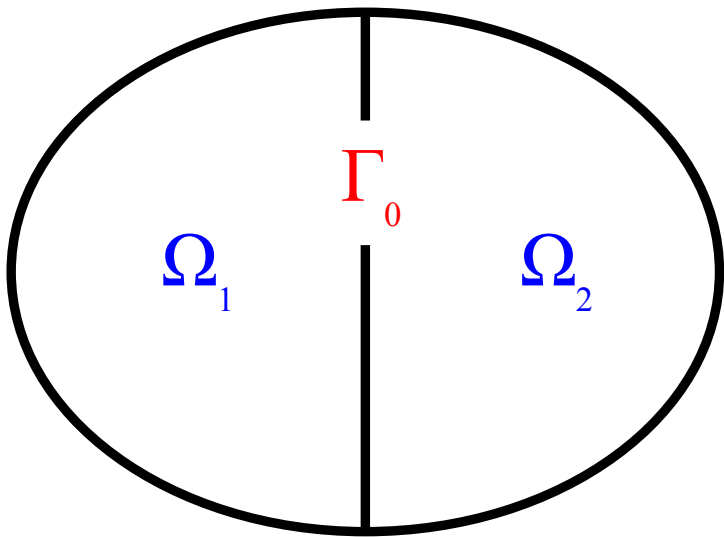


Reduction methods are applicable!

## Problems:

- decomposition not equivalent to overall system
- arising boundaries too large  $\Rightarrow$  multi-level approach







Splitting of state space:

$$\mathbb{R}^n = \mathbb{R}^{n_1} \times \mathbb{R}^{n_2} \times \mathbb{R}^{n_r}$$



$$A = \begin{pmatrix} A_1 & & A_{1,r} \\ & A_2 & A_{2,r} \\ A_{r,1} & A_{r,2} & A_r \end{pmatrix}, \quad E = \begin{pmatrix} E_1 & & E_{1,r} \\ & E_2 & E_{2,r} \\ E_{r,1} & E_{r,2} & E_r \end{pmatrix},$$

$$B = \begin{pmatrix} B_1 \\ B_2 \\ B_r \end{pmatrix}, \quad C = (C_1 \quad C_2 \quad C_r)$$

- $n_r \ll n_i, i = 1, 2$

# Transformation

State space transformation:

$$(\widehat{A}, \widehat{B}, \widehat{C}, \widehat{E}) = (LAR, LB, CR, LER)$$

$$L = \begin{pmatrix} I & & & \\ & I & & \\ -A_{r,1}A_1^{-1} & -A_{r,2}A_2^{-1} & & I \end{pmatrix}, R = \begin{pmatrix} I & & & \\ & I & & \\ & & I & \\ & & & I \end{pmatrix} \begin{pmatrix} -A_1^{-1}A_{1,r} \\ -A_2^{-1}A_{2,r} \\ \\ I \end{pmatrix}$$

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- equivalent realization of the system, i.e.,  $\left[ \begin{array}{c|c} sE - A & B \\ \hline C & \end{array} \right] = \left[ \begin{array}{c|c} s\widehat{E} - \widehat{A} & \widehat{B} \\ \hline \widehat{C} & \end{array} \right]$
- $\widehat{A}$  block-diagonal
- essential parts of matrices don't change
- twosided block-Gaussian elimination (never build  $L$  and  $R$  explicitly)

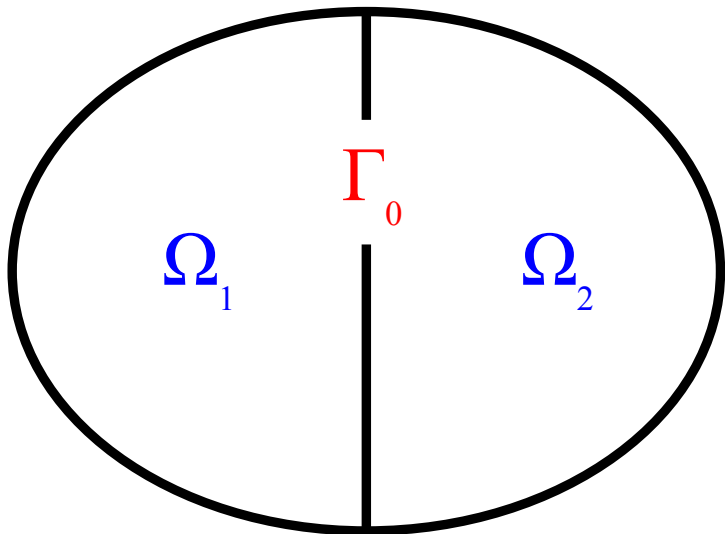
$$\hat{A} = \begin{pmatrix} A_1 & & \\ & A_2 & \\ & & \hat{A}_\Gamma \end{pmatrix}, \hat{E} = \begin{pmatrix} E_1 & & \hat{E}_{1,\Gamma} \\ & E_2 & \hat{E}_{2,\Gamma} \\ \hat{E}_{\Gamma,1} & \hat{E}_{\Gamma,2} & \hat{E}_\Gamma \end{pmatrix}$$

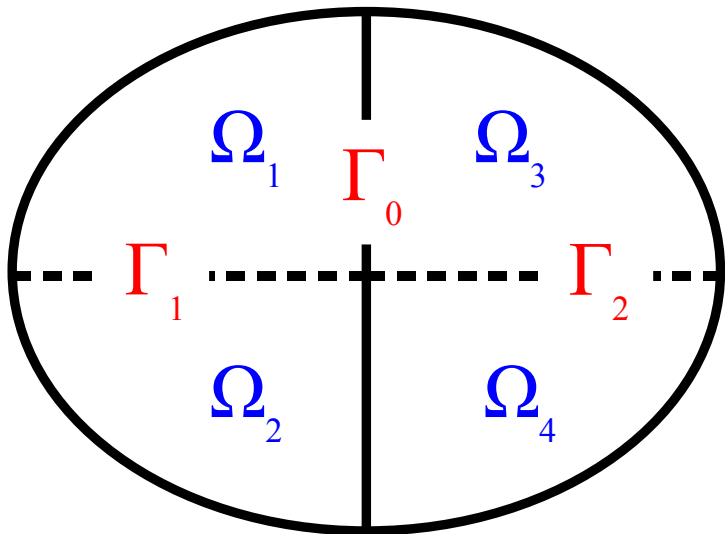
- 1 Subsystems for subdomains  $\Omega_i$ ,  $i = 1, 2$ :

$$G_i = \left[ \begin{array}{c|c} sE_i - A_i & B_i \\ \hline C_i & \end{array} \right]$$

- 2 Subsystem for interface  $\Gamma$ :

$$G_\Gamma = \left[ \begin{array}{c|c} s\hat{E}_\Gamma - \hat{A}_\Gamma & \hat{B}_\Gamma \\ \hline \hat{C}_\Gamma & \end{array} \right],$$





# Nested arrow head structure

$$A = \left( \begin{array}{ccc|cc|c}
 A_1 & & A_{1,\Gamma_1} & & & A_{1,\Gamma_0} \\
 & A_2 & A_{2,\Gamma_1} & & & A_{2,\Gamma_0} \\
 A_{\Gamma_1,1} & A_{\Gamma_1,2} & A_{\Gamma_1} & & & A_{\Gamma_1,\Gamma_0} \\
 \hline
 & & & A_3 & & A_{3,\Gamma_2} & A_{3,\Gamma_0} \\
 & & & & A_4 & A_{4,\Gamma_2} & A_{4,\Gamma_0} \\
 & & & A_{\Gamma_2,3} & A_{\Gamma_2,4} & A_{\Gamma_2} & A_{\Gamma_2,\Gamma_0} \\
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 A_{\Gamma_0,1} & A_{\Gamma_0,2} & A_{\Gamma_0,\Gamma_1} & A_{\Gamma_0,3} & A_{\Gamma_0,4} & A_{\Gamma_0,\Gamma_2} & A_{\Gamma_0}
 \end{array} \right)$$
  

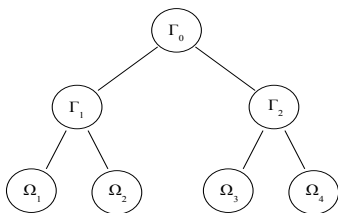
$$E = \left( \begin{array}{ccc|cc|c}
 E_1 & & E_{1,\Gamma_1} & & & E_{1,\Gamma_0} \\
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# Nested arrow head structure

$$\hat{A} = \left( \begin{array}{ccc|cc} A_1 & & & & \\ & A_2 & & & \\ & & \hat{A}_{\Gamma_1} & & \\ \hline & & & A_3 & \\ & & & & A_4 \\ & & & & & \hat{A}_{\Gamma_2} \\ \hline & & & & & & \hat{A}_{\Gamma_0} \end{array} \right)$$

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1 Subdomains:

$$\left[ \begin{array}{c|c} sE_i - A_i & B_i \\ \hline C_i & \end{array} \right], \quad i = 1, \dots, 4$$

2 Interfaces:

$$\left[ \begin{array}{c|c} s\hat{E}_{\Gamma_j} - \hat{A}_{\Gamma_j} & \hat{B}_{\Gamma_j} \\ \hline \hat{C}_{\Gamma_j} & \end{array} \right], \quad j = 0, 1, 2$$

- partitioning is done automatically by a graph partitioner

# Properties of the decomposition

- exact at zero, i.e.,

$$G(0) = \sum_i G_i(0) + \sum_j G_{r_j}(0)$$

- decomposition of the state space is  $A$ -orthogonal in the symmetric case
- derivation from continuous settings  $\Rightarrow$  smoothness condition on interfaces
- “small” parts of the matrix  $\hat{E}$  are ignored

# MLS model order reduction

Principle steps:

- 1 Build subsystems by using multi-level substructuring
- 2 Reduce the subsystems (including interfaces), i.e., determine  $V_i$  and  $W_i$  s.t.

$$G_i^{(k_i)} = \left[ \begin{array}{c|c} sW_i^H \hat{E}_{i,i} V_i - W_i^H \hat{A}_{i,i} V_i & W_i^H \hat{B}_i \\ \hline \hat{C}_i V_i & \end{array} \right]$$

- 3 Project the transformed original system onto

$$\mathcal{V} := \text{colspan}\{V_1\} \times \text{colspan}\{V_2\} \times \dots,$$

i.e.,

$$A_{i,i}^{(k)} = W_i^H \hat{A}_{i,i} V_i,$$

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- $k = \sum_i k_i$
- free choice of reduction method
- applicable in particular if other methods fail due to problem dimension
- multi-level substructuring improves performance for very large systems
- sparse  $B$  or  $C \Rightarrow$  many subsystems may be neglected

Two error sources:

- 1 Reduction of subsystems ← controlled by reduction method
  - 2 Multi-level substructuring
- error sources sum up
  - error due to MLS depends on the projection error of the coupling blocks

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## Consequence

Error may be large even if the subsystems are well approximated!



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  - error sources sum up
  - error due to MLS depends on the projection error of the coupling blocks

## Consequence

Error may be large even if the subsystems are well approximated!

- usually not the case in practical applications

# Remark on reduction by Krylov subspace methods

Problem:

$$\mathcal{V} := \text{colspan}\{V_1\} \times \text{colspan}\{V_2\} \times \dots$$

gets too large

Remedy:

- 1 Perform MLS model order reduction
- 2 Apply the Krylov method a second time to  $(A^{(k)}, B^{(k)}, C^{(k)}, E^{(k)})$

# Second-order systems

$$\begin{aligned} E\ddot{x}(t) + D\dot{x}(t) + Ax(t) &= Bu(t) \\ y(t) &= Cx(t), \end{aligned}$$

- structure preserving model reduction method
- avoid enlargement of the state space

# MLS model order reduction (second-order systems)

- 1 Partition the state space recursively
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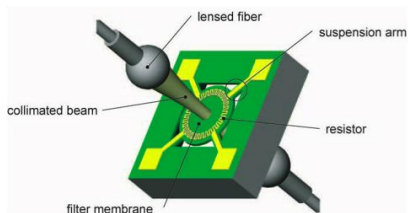
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  - 5 Project the overall system
- equivalent to first-order version applied to system in companion form
  - reduced system has second-order structure
  - other structure may be destroyed

# Tunable optical filter



- optical filter device tuned by thermal means
- spatial discretization of the instationary heat equation yields

$$\begin{aligned} E\dot{x}(t) &= Ax(t) + Bu(t) \\ y(t) &= Cx(t), \end{aligned}$$

- 106.437 state variables, 1 input and 5 outputs

## Partitioning

max. order	SpD	interfaces	domains	levels
500	2	236	237	8

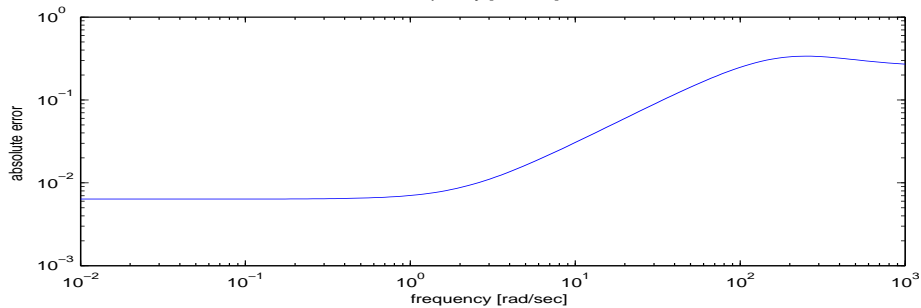
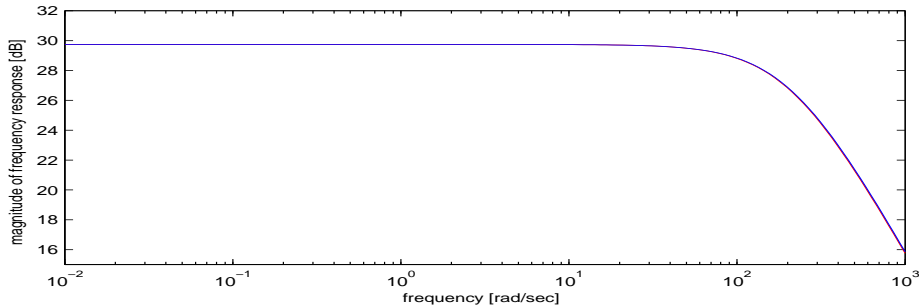
- reduction of subsystems by using balanced truncation
- absolute error tolerance:  $10^{-2}$

## Performance

mem	$t_{par}$	$t_{tr}$	$t_{red}$	$t_{total}$
480 MB	697 sec	489 sec	438 sec	1624 sec

- 457/473 subsystems dropped

reduced order: 15

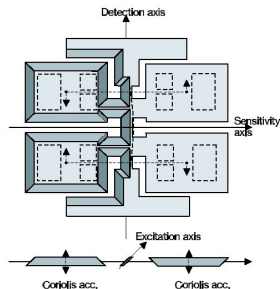


# Butterfly gyro

- micro-mechanical gyroscope
- spatial discretization of elastodynamic equations yields

$$E\ddot{x}(t) + D\dot{x}(t) + Ax(t) = Bu(t),$$
$$y(t) = Cx(t)$$

- 17.361 state variables, 1 input and 12 outputs



## Partitioning

max. order	SpD	interfaces	domains	levels
200	2	80	79	7

- reduction of subsystems by using SOBT

## Performance

mem	$t_{par}$	$t_{tr}$	$t_{red}$	$t_{total}$
330 MB	144 sec	49 sec	12 sec	205 sec

- 151/159 subsystems dropped

reduced order: 40

