Interpolation of parameterized reduced-order models

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Outline

- Parameterized unsteady PDE
- Database approach
- Interpolation of reduced-order bases
- Interpolation of reduced-order matrices
- Applications

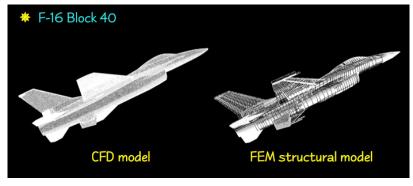
Parametrized unsteady PDE

Linear (linearized) PDE

$$\frac{d\mathbf{w}}{dt}(t) = \mathbf{A}(\boldsymbol{\mu})\mathbf{w}(t) + \mathbf{B}(\boldsymbol{\mu})\mathbf{u}(t)$$

Example: aeroelasticity

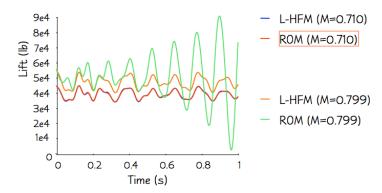
Example: aeroelastic analysis of full aircraft configuration



• Hundreds of flight conditions $\mu = (M_{\infty}, \alpha)$ to clear for flutter

Example: aeroelasticity

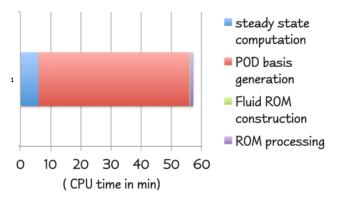
Example



Non-robustness with respect to the operating condition

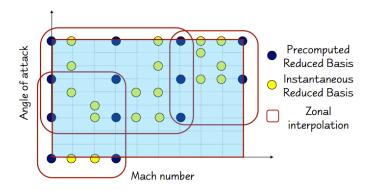
Example: aeroelasticity

Can we afford rebuilding the POD basis?



Not suitable for real-time analysis

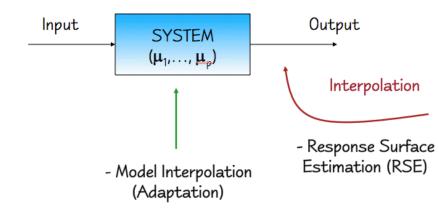
Database approach



What should we interpolate?

Database approach

What should we interpolate?



Model interpolation

Reduced set of equations (after Galerkin projection)

$$\frac{d\mathbf{q}}{dt}(t) = \mathbf{V}(\boldsymbol{\mu})^T \mathbf{A}(\boldsymbol{\mu}) \mathbf{V}(\boldsymbol{\mu}) \mathbf{q}(t) + \mathbf{V}(\boldsymbol{\mu})^T \mathbf{B} \mathbf{u}(t)$$

Full state reconstruction

$$\mathbf{w}(t) \approx \mathbf{V}(\boldsymbol{\mu}) \mathbf{q}(t)$$

- Model: $(\mathbf{V}(\boldsymbol{\mu})^T \mathbf{A}(\boldsymbol{\mu}) \mathbf{V}(\boldsymbol{\mu}), \mathbf{V}(\boldsymbol{\mu})^T \mathbf{B}, \mathbf{V}(\boldsymbol{\mu}))$
- Approach #1:
 - $\mathbf{0}$ interpolate $\mathbf{V}(\boldsymbol{\mu})$

 - evaluate $(\mathbf{A}(\boldsymbol{\mu}), \mathbf{B}(\boldsymbol{\mu}))$ form $(\mathbf{V}(\boldsymbol{\mu})^T \mathbf{A}(\boldsymbol{\mu}) \mathbf{V}(\boldsymbol{\mu}), \mathbf{V}(\boldsymbol{\mu})^T \mathbf{B})$

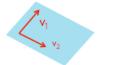
Direct interpolation

- Natural idea: interpolate $\mathbf{V}(\pmb{\mu}) \in \mathbb{R}^{N_{\mathbf{w}} imes k}$ entry-by-entry
- Input:
 - target μ
 - precomputed reduced bases $\{V(\mu_l)\}_{l=1}^m$
 - multi-variate interpolation operator $a(\mu) = \mathcal{I}(\mu; \{a(\mu_l), \mu_l\}_{l=1}^m)$
- Algorithm
 - 1: for $i=1:N_{\mathbf{w}}$ do
 - 2: **for** j = 1 : k **do**
 - 3: Compute $v_{ij}(\boldsymbol{\mu}) = \mathcal{I}(\boldsymbol{\mu}; \{v_{ij}(\boldsymbol{\mu}_l), \boldsymbol{\mu}_l\}_{l=1}^m)$
 - 4: end for
 - 5: end for
 - 6: Form $\mathbf{V}(\boldsymbol{\mu}) = [v_{ij}(\boldsymbol{\mu})]$

Direct interpolation doesn't work

- Example
 - $N_{\mathbf{w}} = 3, k = 2, p = 1$
 - for $\mu_1 = 0$, $\mathbf{V}(0) = [\mathbf{v}_1, \mathbf{v}_2]$
 - for $\mu_2 = 1$, $\mathbf{V}(1) = [-\mathbf{v}_1, \mathbf{v}_2]$
 - target parameter $\mu = 0.5$
 - use linear interpolation
- Interpolation result:

$$V(0.5) = 0.5(V(0) + V(1)) = [0.5(v_1 - v_1), 0.5(v_2 + v_2)] = [0, v_2]$$









- What went wrong?
- We haven't interpolated the correct object

Subspace interpolation

Projection-based model reduction

$$\frac{d\mathbf{q}}{dt}(t) = \mathbf{V}(\boldsymbol{\mu})^T \mathbf{A}(\boldsymbol{\mu}) \mathbf{V}(\boldsymbol{\mu}) \mathbf{q}(t) + \mathbf{V}(\boldsymbol{\mu})^T \mathbf{B} \mathbf{u}(t)$$

ullet Equivalent full state equation (multiply by ${f V}(oldsymbol{\mu}))$

$$\frac{d\mathbf{w}}{dt}(t) = \mathbf{\Pi}_{\mathbf{V}(\boldsymbol{\mu}),\mathbf{V}(\boldsymbol{\mu})}\mathbf{A}(\boldsymbol{\mu})\mathbf{w}(t) + \mathbf{\Pi}_{\mathbf{V}(\boldsymbol{\mu}),\mathbf{V}(\boldsymbol{\mu})}\mathbf{B}\mathbf{u}(t)$$

- An orthogonal projection is independent of the choice of reduced basis associated to the projection subspace
- Important quantity to interpolate: subspace

The Grassmann manifold

- A subspace S is typically represented by a reduced basis
- The choice of reduced basis is not unique

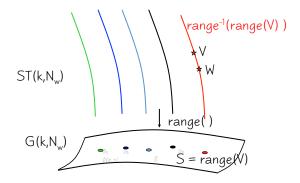
$$S = \text{range}(\mathbf{V}) = \text{range}(\mathbf{V}\mathbf{Q}), \ \forall \mathbf{Q} \in \mathsf{GL}(k)$$

- Matrix manifolds of interest
 - $\mathcal{G}(k, N_{\mathbf{w}})$ (Grassmann manifold): set of subspaces of dimension k in $\mathbb{R}^{N_{\mathbf{w}}}$
 - $\mathcal{ST}(k, N_{\mathbf{w}})$ (orthogonal Stiefel manifold): set of orthogonal reduced bases of dimension k in $\mathbb{R}^{N_{\mathbf{w}}}$
- Case of model reduction
 - $\mathbf{V}(\boldsymbol{\mu}) \in \mathcal{ST}(k, N_{\mathbf{w}})$
 - range $(\mathbf{V}(\boldsymbol{\mu})) \in \mathcal{G}(k, N_{\mathbf{w}})$
- Interpolation on the Grasmann manifold (quotient manifold) using quantities belonging to the Stiefel manifold

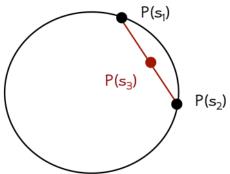
$$\mathcal{G}(k, N_{\mathbf{w}}) = \mathcal{ST}(k, N_{\mathbf{w}}) / \mathcal{O}(k)$$

The Grassmann manifold

- Matrix manifolds of interest
 - $\mathcal{G}(k,N_{\mathbf{w}})$ (Grassmann manifold): set of subspaces of dimension k in $\mathbb{R}^{N_{\mathbf{w}}}$
 - $\mathcal{ST}(k, N_{\mathbf{w}})$ (orthogonal Stiefel manifold): set of orthogonal reduced bases of dimension k in $\mathbb{R}^{N_{\mathbf{w}}}$



First example: the circle



- Standard interpolation fails
- Idea: interpolate on a linear space ⇒ a tangent space to the manifold

- Input:
 - precomputed matrices $\{\mathbf{A}(oldsymbol{\mu}_l)\}_{l=1}^m$
 - multi-variate interpolation operator $a(\mu) = \mathcal{I}(\mu; \{a(\mu_l), \mu_l\}_{l=1}^m)$
 - map $m_{\mathbf{A}}$ from the manifold ${\mathcal{M}}$ to the tangent space of ${\mathcal{M}}$ at $m_{\mathbf{A}}$
 - inverse map $m_{\mathbf{A}}^{-1}$ from the tangent space to $\mathcal M$ at $m_{\mathbf{A}}$ to the manifold $\mathcal M$

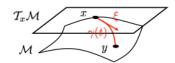
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1: for l = 1 : m do
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- 2: Compute $\Gamma(\mu_l) = m_{\mathbf{A}}(\mathbf{A}(\mu_l))$
- 3: end for
- 4: for $i = 1 : N_{\mathbf{w}}$ do
- 5: **for** j = 1 : k **do**
- 6: Compute $\Gamma_{ij}(\boldsymbol{\mu}_l) = \mathcal{I}(\boldsymbol{\mu}; \{\Gamma_{ij}(\boldsymbol{\mu}_l), \boldsymbol{\mu}_l\}_{l=1}^m)$
- 7: end for
- 8: end for
- 9: Form $\Gamma(\mu)=[\Gamma_{ij}(\mu)]$ and compute $\mathbf{A}(\mu)=m_{\mathbf{A}}^{-1}(\Gamma(\mu))$
 - Requirement: the interpolation operator \mathcal{I} preserves the tangent space.

$$\text{for instance:} \quad a(\boldsymbol{\mu}) = \mathcal{I}(\boldsymbol{\mu}; \{a(\boldsymbol{\mu}_l), \boldsymbol{\mu}_l\}_{l=1}^m) = \sum_{l=1}^m \theta_l(\boldsymbol{\mu}) a(\boldsymbol{\mu}_l)$$

- How do we find $m_{\mathbf{A}}$ and its inverse $m_{\mathbf{A}}^{-1}$
- Idea: use concepts from differential geometry
- Geodesics
 - generalize straight lines on manifolds
 - uniquely defined given a point x of the manifold and a tangent vector ξ at this point

$$\gamma(t; x, \xi) : [0, 1] \to \mathcal{M}$$
$$\gamma(0; x, \xi) = x, \ \dot{\gamma}(0, x, \xi) = \xi$$



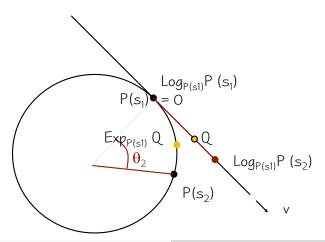
Exponential map

$$\mathsf{Exp}_x: \mathcal{T}_x\mathcal{M} \to \mathcal{M} \ \xi \longmapsto \gamma(1; x, \xi)$$

• Logarithm map (defined in a neighborhood \mathcal{U}_x of x)

$$\mathsf{Log}_x : \mathcal{U}_x \subset \mathcal{M} \to \mathcal{T}_x \mathcal{M} \ y \longmapsto \mathsf{Exp}_x^{-1}(y)$$

Application to interpolation of points on a circle



Case of the Grassmann manifold

- Logarithmic map
 - Compute the thin SVD

$$(\mathbf{I} - \mathbf{V}_0 \mathbf{V}_0^T) \mathbf{V}_1 (\mathbf{V}_0^T \mathbf{V}_1)^{-1} = \mathbf{U} \mathbf{\Sigma} \mathbf{Z}^T$$

Compute

$$\mathbf{\Gamma} = \mathbf{U} \tan^{-1}(\mathbf{\Sigma}) \mathbf{Z}^T$$

- $lackbox{0} \ \mathsf{Log}_{\mathcal{S}_0}(\mathcal{S}_1) \leftrightarrow \mathbf{\Gamma}$
- Exponential map of $oldsymbol{\xi} \in \mathcal{T}_{\mathcal{S}_0}\mathcal{G} \leftrightarrow oldsymbol{\Gamma}$
 - Compute the thin SVD

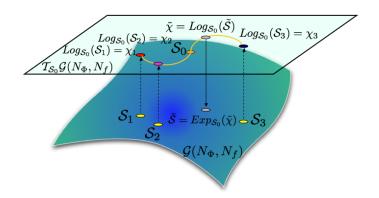
$$\mathbf{\Gamma} = \mathbf{U}\mathbf{\Sigma}\mathbf{Z}^T$$

Compute

$$\mathbf{V} = \mathbf{V}_0 \mathbf{Z} \cos \mathbf{\Sigma} + \mathbf{U} \sin \mathbf{\Sigma}$$

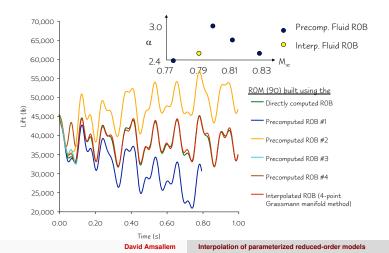
- lacksquare Exp_{S0}($m{\xi}$) = range($f{V}$)
- Note: the trigonometric operators only apply to the diagonal elements of the matrices

Case of the Grassmann manifold



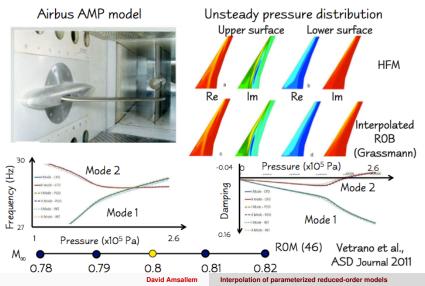
Application to aeroelasticity

Aeroelastic behavior of the F-16



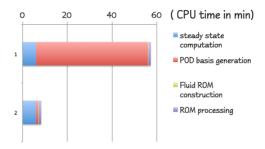
Application to aeroelasticity

Aeroelastic behavior a commercial aircraft



Application to aeroelasticity

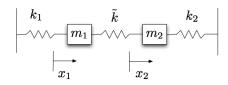
Aeroelastic behavior of the F-16



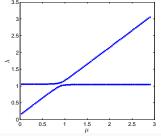
- Dominant cost: computation of $A(\mu)$ and $B(\mu)$ for a new value of μ
- Approach #2: interpolate $(\mathbf{V}(\pmb{\mu})^T\mathbf{A}(\pmb{\mu})\mathbf{V}(\pmb{\mu}),\mathbf{V}(\pmb{\mu})^T\mathbf{B}(\pmb{\mu}))$

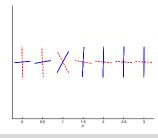
Example

- Simple example: mass-spring system with two degrees of freedom
- $\mu = k_1 0.1$



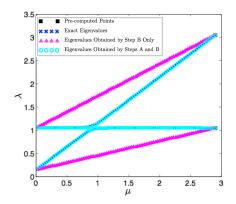
 $\bullet \ \mathbf{V}(\boldsymbol{\mu})^T \mathbf{A}(\boldsymbol{\mu}) \mathbf{V}(\boldsymbol{\mu}) = \boldsymbol{\Lambda}(\boldsymbol{\mu})$





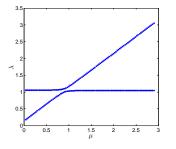
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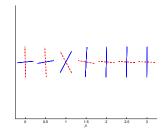
- $\Lambda(\mu)$ belongs to the manifold of symmetric positive definite matrices (diagonal)
- Interpolate on the manifold using $(\Lambda(0), \Lambda(2.9))$



Example: Mode veering and mode crossing

 The issue is the mode veering: the coordinates of the reduced matrices are not consistent





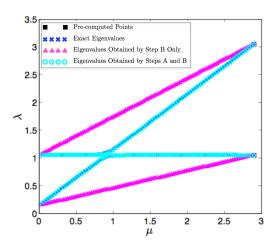
• There would be an issue also with mode crossing (the eigenfrequencies are ordered increasingly in Λ)

Consistent interpolation on matrix manifolds

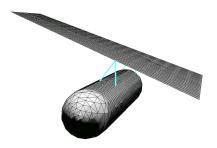
- Solution: pre-process the reduced matrices (Step A)
- Consistency enforced by the solution of an orthogonal Procrustes problem

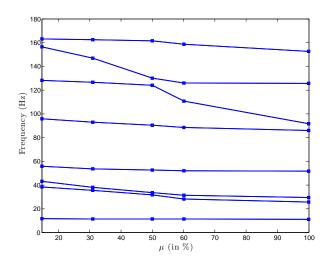
$$\min_{\mathbf{Q}_i \ \mathbf{Q}_i^T \mathbf{Q}_i = \mathbf{I}_k} \| \mathbf{V}_i \mathbf{Q}_i - \mathbf{V}_{i_0} \|_F, \ \forall i = 1, \cdots, m$$

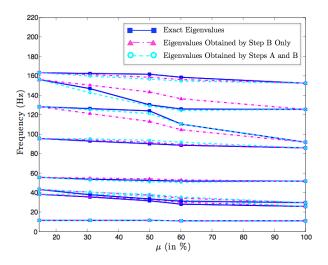
- Analytical solution using the SVD
 - Ompute $\mathbf{P}_{i,i_0} = \mathbf{V}_i^T \mathbf{V}_{i_0}$
 - Ompute the SVD $\mathbf{P}_{i,i_0} = \mathbf{U}_{i,i_0} \mathbf{\Sigma}_{i,i_0} \mathbf{Z}_{i,i_0}^T$
- Can be processed online or offline
- Step B: interpolation on a matrix manifold



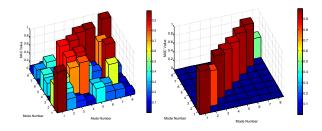
- More challenging example: wing with tank and sloshing effect
- The hydro-elastic effects affect the eigen-frequencies and eigen-modes of the structure
- The parameter μ defines the level of fuel in the tank $0 \le \mu \le 100\%$







Link with Modal Assurance Criterion

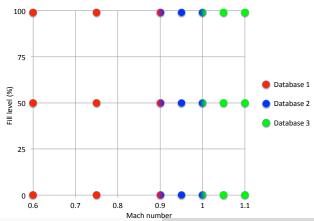


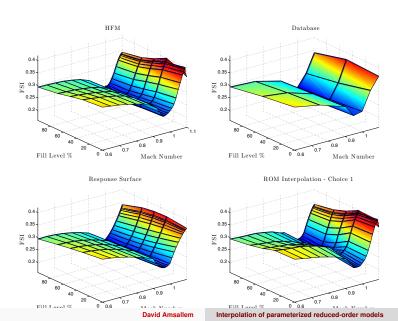
ullet The MAC between two eigenmodes ϕ and ψ is

$$\mathsf{MAC}(\boldsymbol{\phi}, \boldsymbol{\psi}) = \frac{|\boldsymbol{\phi}^T \boldsymbol{\psi}|^2}{(\boldsymbol{\phi}^T \boldsymbol{\phi})(\boldsymbol{\psi}^T \boldsymbol{\psi})}$$

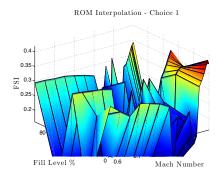
- When ϕ and ψ are normalized MAC $(\phi, \psi) = |\phi^T \psi|^2$
- P_{i,i_0} is the matrix of square roots of the MACs between the modes contained in $V(\mu_i)$ and those contained in $V(\mu_{i_0})$.
- This is the Modal Assurance Criterion Square Root (MACSR)

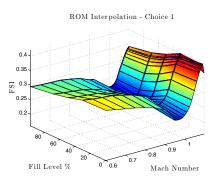
- Aeroelastic study of the wing-tank system
- ullet 2 parameters: fill level and free-stream Mach number M_{∞}
- Database approach



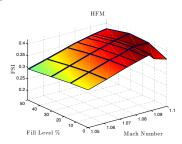


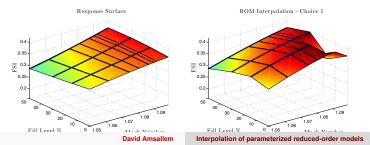
· Effect of Step A



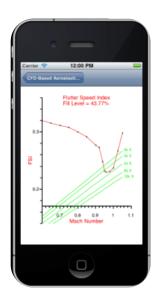


Bifurcation detection





Mobile computing using a database of ROMs



References

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- D. Amsallem, C. Farhat: An online method for interpolating linear parametric reduced- order models. SIAM Journal on Scientific Computing 33(5), 2169–2198 (2011)
- D. Amsallem, Interpolation on Manifolds of CFD-based Fluid and Finite Element-based Structural Reduced-order Models for On-line Aeroelastic Prediction, PhD thesis, Stanford University (2010)