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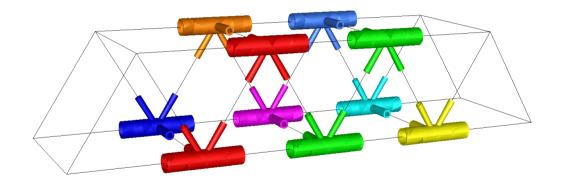
Jacket joints

- Jacket structures used in marine operations are subject to rigorous compliance standards
- Much time is spent solving linear elasticity problems on such structures
- Beams are modeled cheaply using beam elements but the joints are not
- Want a joint ROM parametrized on material properties and geometry (plate thickness, radius, beam angles etc)





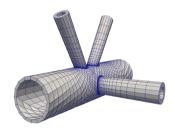
Example





Static condensation

- Static condensation 'compresses' each component to a $6n \times 6n$ superelement that acts as coupling terms between otherwise disconnected beam elements.
- Works well if each component is identical.
- Still requires the solution of a nontrivial system.
- Not parametrized over geometry, material, etc.





Static condensation

$$\begin{pmatrix} \mathbf{A}_{BB} & \mathbf{A}_{BI} \\ \mathbf{A}_{IB} & \mathbf{A}_{II} \end{pmatrix} \begin{pmatrix} \mathbf{u}_B \\ \mathbf{u}_I \end{pmatrix} = \begin{pmatrix} \mathbf{f}_B \\ \mathbf{f}_I \end{pmatrix}$$

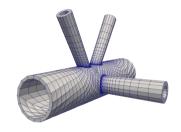
$$\mathbf{A}_{II} \mathbf{u}_I = \mathbf{f}_I - \mathbf{A}_{IB} \mathbf{u}_B$$

$$(\mathbf{A}_{BB} - \mathbf{A}_{BI} \mathbf{A}_{II}^{-1} \mathbf{A}_{IB}) \mathbf{u}_B = \mathbf{f}_B - \mathbf{A}_{BI} \mathbf{A}_{II}^{-1} \mathbf{f}_I$$



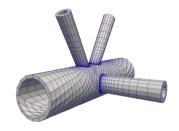
The technique follows in brief Eftang and Patera (2013).

- For each port, six ROMs are constructed each evaluating the response on the structure from one degree of freedom on the boundary (three translations and three rotations)
- In addition, one ROM is constructed with homogeneous boundary conditions, evaluating the response from other sources, e.g. gravity





- In the online stage, each of the 6n ROMs are queried and the solutions form the internal basis functions for a $6n \times 6n$ superelement matrix
- The solution to the homogenous ROM enters the right hand side as a load term
- Parametrized and faster static condensation





Let

- $\ell^{(i)}$ be the lifting function associated with port i
- ullet $\left\{b_k^{(i)}\right\}_k$ be reduced basis functions associated with port i

Then the response due to excitation of port i is

$$\begin{split} \Psi^{(i)} &= \ell^{(i)} + \sum_k c_k b_k^{(i)} \\ a(\Psi^{(i)}, v) &= 0 \quad \forall v \end{split}$$

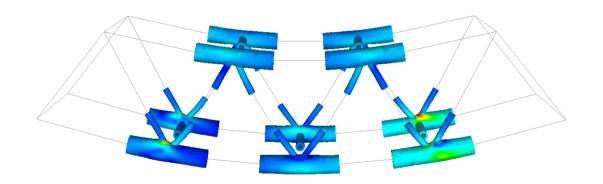


And the contribution to the (Galerkin) superelement is

$$\begin{split} a(\Psi^{(i)}, \Psi^{(j)}) &= a\left(\Psi^{(i)}, \ell^{(j)} + \sum_{l} c_{l} b_{l}^{(j)}\right) \\ &\approx a\left(\Psi^{(i)}, \ell^{(j)}\right) \\ &= a\left(\ell^{(i)}, \ell^{(j)}\right) + \sum_{k} c_{k} a\left(b_{k}^{(i)}, \ell^{(j)}\right) \end{split}$$

where we can discard the expensive terms due to (approximate) Galerkin orthogonality.

Example





Intrusiveness

- Many decisions made in the following are motivated by non-intrusiveness
- RBMs are typically quite intrusive: to reduce a FOM requires expert knowledge of it
- We aim to deliver a generalized RBM software package (AROMA) that is as non-intrusive as possible
 - snapshots as fully-featured solution vectors
 - stiffness matrix and load vector in restricted sense (i.e. with fixed DoFs removed and lift applied) — avaliable as debug output in most FOM software
 - knowledge of DoF classification (fixed/free) and lift fairly mundane
- Aim is to view the FOM as a nearly opaque black box

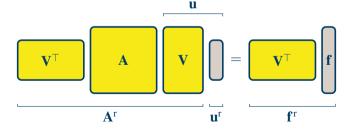


Reduced basis methods

Substitute the solution of a large system

$$egin{array}{c} \mathbf{A} & \mathbf{u} \end{bmatrix} = egin{bmatrix} \mathbf{f} \end{bmatrix}$$

with a smaller one





Solution and assembly

- Extremely fast solutions in the online stage: ${\bf A}^{\rm r}(\mu)$ frequently on the order of $\sim 10 \times 10$ or so.
- ullet Assembly of ${f A}^{
 m r}(\mu)$ remains an open issue. On the face of it,

$$\mathbf{A}^{\mathrm{r}}(\mu) = \mathbf{V}^{\top} \mathbf{A}(\mu) \mathbf{V}$$

requires the construction of the full-order matrix $\mathbf{A}(\mu)$ in the online stage.

Many solutions have been proposed, most of which relates to...



The assumption of affine parametric dependence

If $\mathbf{A}(\mu)$ takes the form

$$\mathbf{A}(\mu) = \sum_{i} \xi_{i}(\mu) \mathbf{A}_{i}$$

then $A^{r}(\mu)$ takes the form

$$\mathbf{A}^{\mathrm{r}}(\boldsymbol{\mu}) = \mathbf{V}^{\top} \mathbf{A}(\boldsymbol{\mu}) \mathbf{V} = \sum_{i} \xi_{i}(\boldsymbol{\mu}) \mathbf{V}^{\top} \mathbf{A}_{i} \mathbf{V} = \sum_{i} \xi_{i}(\boldsymbol{\mu}) \mathbf{A}_{i}^{\mathrm{r}}$$

Each A_i^r is small and easily storeable. Assuming the ξ_i are not pathological and the sum not too long, assembly in this form is competitive with time spent solving the system.

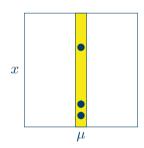
The assumption of affine parametric dependence

- Affinity tends to hold well with
 - explicit material parameters: elastic properties, viscosities, thermal conductivities
 - load and boundary data
- But not with geometric variability
 - even simple variation manifests in the integrands (for FEM) or fluxes (for FVM) in nontrivial ways (Fonn et. al., 2018)
- Approximate affine parametric dependence can be forced using various interpolation methods



Empirical Interpolation

- EIM requires the online stage to evaluate a function $g(x,\mu)$ at certain points x in the physical domain, or a vector-valued function $g_i(\mu)$ at certain entries i.
- \bullet Here, g is the Finite Element variational form or similar for FVM
- In the black-box FOM context we operate in, such restricted evaluation of the integrand is not possible (too intrusive)
- Instead, we resort to Matrix Least Squares





Matrix Least Squares

Given reasonable guesses for $\xi_i(\mu)$, compute corresponding coefficient matrices ${\bf A}_i$ by minimizing

$$\int_{\mu} \left\| \mathbf{A}(\mu) - \sum_{i} \xi_{i}(\mu) \mathbf{A}_{i} \right\|_{2}^{2} \mathrm{d}\mu.$$

In practice, this is implemented the same was as conventional L^2 -fit on a sampling over μ :

$$\begin{split} \mathbf{B}_{ji} &= \xi_i(\mu_j) \\ \mathbf{A}_i &= \sum_{jk} (\mathbf{B}^{\top} \mathbf{B})_{ik}^{-1} \mathbf{B}_{jk} \mathbf{A}(\mu_j) \end{split}$$



Matrix Least Squares

- In practice, sampling A, f is done at the same time, and in the same parameter values as the snapshots.
- If the sampling strategy is known in advance, the contribution from $\mathbf{A}(\mu_j)$ can be immediately applied and the matrix then discarded.
- Much leeway is admitted in the choice of ξ_i
 - known affinities may be exploited, e.g.

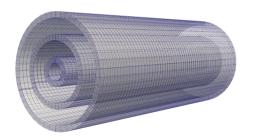
$$\xi_1(E,\nu) = \frac{E}{2(1+\nu)}, \qquad \xi_2(E,\nu) = \frac{E}{(1-2\nu)(1+\nu)}$$

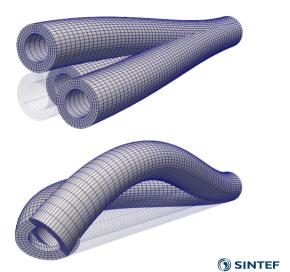
- orthogonal polynomial families as a last resort, $\xi_i(r) = P_i(r)$
- a combination, $\xi_i(E,\nu)=EP_i(\nu)$

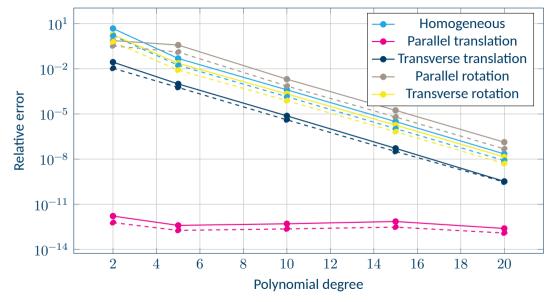


Example: two-port cylinder

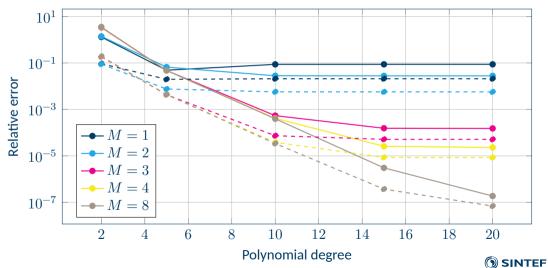
Minimal example with variable radius



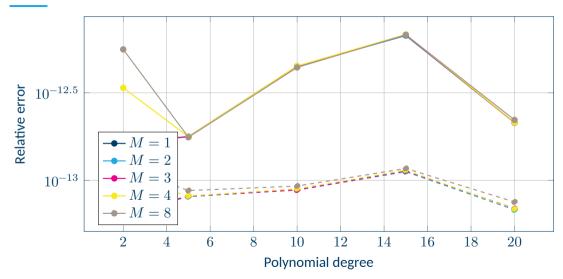




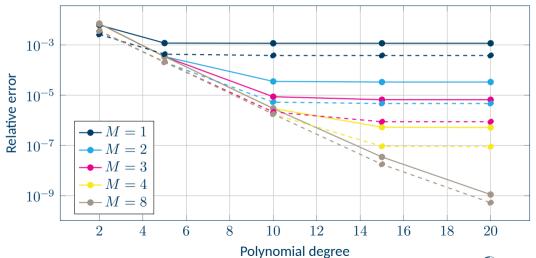
Homogenous case



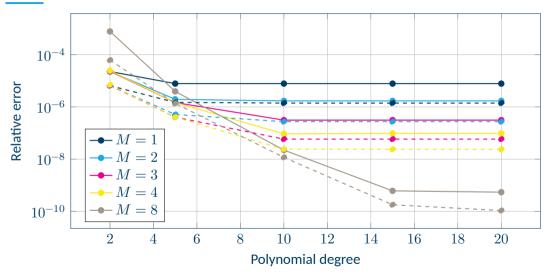
Parallel translation case



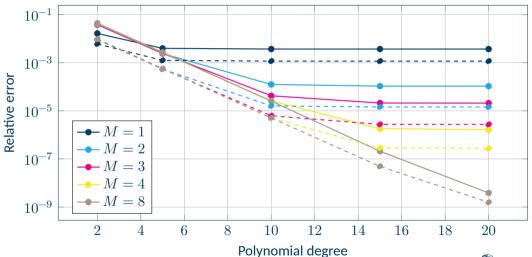
Transverse translation case



Parallel rotation case



Transverse rotation case



Wish list

- Ability to both
 - not plan sampling scheme in advance, and
 - be able use and discard matrices on-the-fly
- Discover suitable ξ automatically
- Maintain black-box treatment of FOM
- Some more complicated case studies (meshing challenges)



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