



Solveurs performants pour les fonctionnelles énergétiques

Résumé des travaux de recherche effectués au Scientific Computing Laboratory, University of Minnesota 13 juin 2017

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Overview

- 1 The constrained optimization problem
 - ► Construction of the hybrid model
 - energy-based minimization
- 2 Solving the saddle-point linear system
 - Nullspace projection
 - ▶ Iterative methods & block preconditioning
 - ► Numerical results
- 3 Conclusions and perspectives





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Construction of the hybrid model

Ingredients

- ► Hybrid model = numerical model + experimental model
- ► Finite element numerical model of the structure with the mass matrix $M = M(\theta) \in R^n$ and the stiffness matrix $K = K(\theta) \in R^n$
- ► Each numerical couple of eigenvalue and eigenvector $(\omega_{\theta}, \varphi_{\theta})$ satisfies :

$$(K(\theta) - \omega_{\theta}^2 M(\theta))\varphi_{\theta} = 0, \varphi_{\theta} \neq 0$$

- Experimental modal basis is available $(\omega_{exp}, \phi_{exp})$
- → Expansion of the experimental modes on the numerical model in order to compute the response







- ho is the best estimation of φ_{θ} , minimizing the distance with the ϕ_{exp} at the pulsation ω_{exp} .
- lacktriangledown ψ is an error in stiffness in the model. It satisfies :

$$K(\theta)\psi = (K(\theta) - \omega_{exp}^2 M(\theta))\varphi,$$



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▶ Quadratic problem → Model error + numerical/experimental distance

$$e_{\omega}(\varphi, \psi, \theta) = \frac{1}{2} \psi^{\mathsf{T}} \mathsf{K}(\theta) \psi + \frac{r}{2(1-r)} (\mathsf{\Pi} \varphi - \phi_{\mathsf{exp}})^{\mathsf{T}} \mathsf{K}_{r} (\mathsf{\Pi} \varphi - \phi_{\mathsf{exp}})$$





Minimizing the cost function :

$$\begin{cases}
f_{\omega}(\varphi, \psi, \lambda, \lambda_{1}, \lambda_{2}, \theta) = e_{\omega}(\varphi, \psi, \theta) + c_{\omega}(\varphi, \psi, \lambda, \lambda_{1}, \lambda_{2}, \theta) \\
c_{\omega}(\varphi, \psi, \lambda, \lambda_{1}, \lambda_{2}, \theta) = \lambda^{T}((K(\theta) - \omega_{\exp}^{2}M(\theta))\varphi - K(\theta)\psi) - \lambda_{1}^{T}C\psi + \lambda_{2}^{T}(C\psi)
\end{cases}$$

Stationarity conditions :

Stationarity conditions:
$$\begin{cases} \frac{\partial f_{\omega}}{\partial \varphi} = 0 \iff \frac{r}{1-r} \Pi^T K_r (\Pi \varphi - \phi_{\text{exp}}) + (K(\theta) - \omega_{\text{exp}}^2 M(\theta)) \lambda - C^T \lambda_2 = 0 \\ \frac{\partial f_{\omega}}{\partial \psi} = 0 \iff K(\theta) \psi - K(\theta) \lambda + C^T \lambda_2 - C^T \lambda_1 = 0 \end{cases}$$
$$\begin{cases} \frac{\partial f_{\omega}}{\partial \psi} = 0 \iff -K(\theta) \psi + (K(\theta) - \omega_{\text{exp}}^2 M(\theta)) \varphi = 0 \\ \frac{\partial f_{\omega}}{\partial \lambda_1} = 0 \iff C \psi = 0 \end{cases}$$
$$\frac{\partial f_{\omega}}{\partial \lambda_2} = 0 \iff C \psi - C \varphi = 0$$





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Minimizing the cost function yields the following saddle-point linear system:

$$\begin{bmatrix} -K(\theta) & -C^T & K(\theta) - \omega_{exp}^2 M(\theta) & C^T \\ -C & 0 & C & 0 \\ K(\theta) - \omega_{exp}^2 M(\theta) & C^T & \frac{r}{1-r} \Pi^T K_r \Pi & 0 \\ C & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \psi \\ \lambda_1 \\ \varphi \\ \lambda_2 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ \frac{r}{1-r} \Pi^T K_r \phi_{exp} \\ 0 \end{bmatrix}$$





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▶ If we consider the constrained stiffness and mass matrices :

$$\widetilde{K} = \begin{bmatrix} K(\theta) & C^T \\ C & 0 \end{bmatrix}, \quad \widetilde{M} = \begin{bmatrix} M(\theta) & 0 \\ 0 & 0 \end{bmatrix}$$

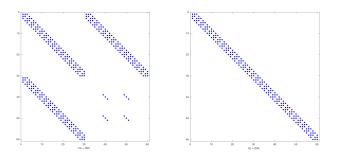
Then:

$$\begin{bmatrix} -\widetilde{K}(\theta) & \widetilde{K}(\theta) - \omega_{\exp}^2 \widetilde{M}(\theta) \\ \widetilde{K}(\theta) - \omega_{\exp}^2 \widetilde{M}(\theta) & \frac{r}{1-r} \widetilde{\Pi}^T \widetilde{K}_r \widetilde{\Pi} \end{bmatrix} \begin{bmatrix} \widetilde{\psi} \\ \widetilde{\varphi} \end{bmatrix} = \begin{bmatrix} \widetilde{0} \\ \frac{r}{1-r} \widetilde{\Pi}^T \widetilde{K}_r \widetilde{\phi}_{\exp} \end{bmatrix}$$





- Nonsingular matrix
- ▶ But : Large band, bad fill-in ratio, highly indefinite ...



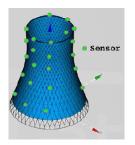
The pattern of the studied saddle point matrix (left) and a finite element matrix in (right)





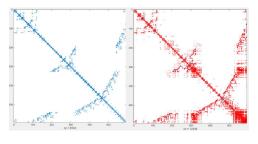
Mechanical solvers

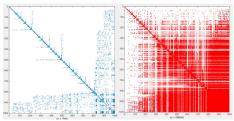
▶ for an industrial structure model with more than 10^6 dofs and few hundreds of measurement points (i.e. $N \approx 10^6$ and $n \approx 100$), MD Nastran® provides a huge computation cost for a single calculation.





Direct mechanical solvers









The linear system could be described in equivalent form as follows:

$$A = \begin{bmatrix} -A & -C^T & B^T & C^T \\ -C & 0 & C & 0 \\ B & C^T & T & 0 \\ C & 0 & 0 & 0 \end{bmatrix} \equiv \begin{bmatrix} -A & B^T & -C^T & C^T \\ B & T & C^T & 0 \\ \hline -C & C & 0 & 0 \\ C & 0 & 0 & 0 \end{bmatrix} = \begin{bmatrix} \tilde{A} & \tilde{C}^T \\ \tilde{C} & 0 \end{bmatrix}$$

where
$$A = K(\theta) \in \mathbb{R}^{n \times n}$$
, $B = K(\theta) - \omega_{exp}^2 M(\theta) \in \mathbb{R}^{n \times n}$ and $T = \frac{r}{1-r} \Pi^T K_r \Pi$.

The fundamental nullspace basis of \widehat{C} , is described using :

- $-\widetilde{Z} \in \mathbb{R}^{2n \times 2(n-m)}$ such that $range(\widetilde{Z}) = Ker(\widetilde{C})$
- $-\widetilde{Y} \in \mathbb{R}^{2n \times 2m}$ such that $Im(\widetilde{Y}) = Im(\widetilde{C}^T)$. We can take $\widetilde{Y} = \widetilde{C}^T$ which is the description of $Im(\widetilde{C}^T)$ in canonical basis.

$$NB = \begin{bmatrix} \widetilde{C}^T & \widetilde{Z} & 0 \\ 0 & 0 & \mathbb{I}_{2m} \end{bmatrix}$$





► The equivalent linear system is as follows :

$$\mathcal{A} \equiv \left[\begin{array}{ccc} \widetilde{C} & 0 \\ \widetilde{Z}^T & 0 \\ 0 & \mathbb{I}_{2m} \end{array} \right] \left[\begin{array}{ccc} \widetilde{A} & \widetilde{C}^T \\ \widetilde{C} & 0 \end{array} \right] \left[\begin{array}{ccc} \widetilde{C}^T & \widetilde{Z} & 0 \\ 0 & 0 & \mathbb{I}_{2m} \end{array} \right] = \left[\begin{array}{ccc} \widetilde{C}\widetilde{A}\widetilde{C}^T & \widetilde{C}\widetilde{A}\widetilde{Z} & \widetilde{C}\widetilde{C}^T \\ \widetilde{Z}^T\widetilde{A}\widetilde{C}^T & \widetilde{Z}^T\widetilde{A}\widetilde{Z} & 0 \\ \widetilde{C}\widetilde{C}^T & 0 & 0 \end{array} \right]$$



► The equivalent linear system is as follows :

$$\mathcal{A} \equiv \left[\begin{array}{cc} \widetilde{C} & 0 \\ \widetilde{Z}^{T} & 0 \\ 0 & \mathbb{I}_{2m} \end{array} \right] \left[\begin{array}{cc} \widetilde{A} & \widetilde{C}^{T} \\ \widetilde{C} & 0 \end{array} \right] \left[\begin{array}{cc} \widetilde{C}^{T} & \widetilde{Z} & 0 \\ 0 & 0 & \mathbb{I}_{2m} \end{array} \right] = \left[\begin{array}{cc} \widetilde{C}\widetilde{A}\widetilde{C}^{T} & \widetilde{C}\widetilde{A}\widetilde{Z} & \widetilde{C}\widetilde{C}^{T} \\ \widetilde{Z}^{T}\widetilde{A}\widetilde{C}^{T} & \widetilde{Z}^{T}\widetilde{A}\widetilde{Z} & 0 \\ \widetilde{C}\widetilde{C}^{T} & 0 & 0 \end{array} \right]$$

Let $Z \in R^{n \times (n-m)}$ be a matrix such that range(Z) = Ker(C). It is trivial to see that $\widetilde{Z} = \begin{bmatrix} Z & 0 \\ 0 & Z \end{bmatrix}$ where Im(Z) = Ker(C). We obtain that :

$$\widetilde{Z}^T \widetilde{A} \widetilde{Z} = \begin{bmatrix} Z & 0 \\ 0 & Z \end{bmatrix}^T \begin{bmatrix} -A & B \\ B & T \end{bmatrix} \begin{bmatrix} Z & 0 \\ 0 & Z \end{bmatrix} = \begin{bmatrix} -Z^T A Z & Z^T B Z \\ Z^T B Z & Z^T T Z \end{bmatrix}$$





Computing a sparse nullspace basis of C

▶ Using skinny LU technique : Perform LU on the "skinny" matrix C^T

$$PC^TQ = \begin{bmatrix} L_1 \\ L_2 \end{bmatrix} U_1$$

where P and Q are permutations, and define the nulspace to be :

$$Z = P^T \left[\begin{array}{c} -L_1^{-T} L_2^T \\ \mathbb{I} \end{array} \right]$$

► Implementation of a fast sparse nullspace basis generation algorithm on SuperLU





► The reduced linear system to solve is :

$$\begin{bmatrix} -Z^T A Z & Z^T B Z \\ Z^T B Z & Z^T T Z \end{bmatrix} \begin{bmatrix} x_{Z1} \\ x_{Z2} \end{bmatrix} = \begin{bmatrix} -A_Z & B_Z \\ B_Z & T_Z \end{bmatrix} \begin{bmatrix} x_{Z1} \\ x_{Z2} \end{bmatrix} = \begin{bmatrix} 0 \\ f_Z \end{bmatrix}$$

▶ The coefficient matrix is also a saddle point one, where $\mathbb{A}_{\mathbb{Z}}$ is SPD, $\mathbb{B}_{\mathbb{Z}}$ is a symmetric indefinite matrix that shares the same pattern as $\mathbb{A}_{\mathbb{Z}}$, and $\mathbb{T}_{\mathbb{Z}}$ is symmetric positive semidefinite, composed of a dense $c \times c$ sub-block scattered into a $n \times n$ matrix, where c << n is the number of sensors.



The constraint preconditioner

► We use the following decomposition of the constraint preconditioner :

$$P = \begin{bmatrix} -G_Z & B_Z \\ B_Z & T_Z \end{bmatrix} = \begin{bmatrix} \mathbb{I}_{n-m} & 0 \\ -B_Z G_Z^{-1} & S_Z \end{bmatrix} \begin{bmatrix} -G_Z & B_Z \\ 0 & \mathbb{I}_{n-m} \end{bmatrix}$$

$$P = \begin{bmatrix} -G_Z^{-1} & G_Z^{-1} B_Z \\ 0 & \mathbb{I}_{n-m} \end{bmatrix}$$

$$P^{-1} = \begin{bmatrix} -G_Z^{-1} & G_Z^{-1} B_Z \\ 0 & \mathbb{I}_{n-m} \end{bmatrix} \begin{bmatrix} \mathbb{I}_{n-m} & 0 \\ S_Z^{-1} B_Z G_Z^{-1} & S_Z^{-1} \end{bmatrix}$$

where $S_Z = T_Z + B_Z G_Z^{-1} B_Z$ is the shur complement of $-G_Z$.





The constraint preconditioner P_1

- ▶ A_Z is positive definite, we take $G_Z = L_A L_A^T$ a Cholesky decomposition as an approximation. We use $D = Diag(A_Z)$ instead of G_Z in the shur complement which admits a Cholesky factorisation $\widetilde{S}_Z = L_S L_S^T$.
- ightharpoonup Applying these approximations, we get the preconditioner P_1 :

$$P_1^{-1} \equiv \begin{bmatrix} -L_A^{-T} L_A^{-1} & L_A^{-T} L_A^{-1} B_Z \\ 0 & \mathbb{I}_{n-m} \end{bmatrix} \begin{bmatrix} \mathbb{I}_{n-m} & 0 \\ L_S^{-T} L_S^{-1} B_Z D^{-1} & L_S^{-T} L_S^{-1} \end{bmatrix}$$



The constraint preconditioner P_2

► An other way to approximate the Shur complement in our case, is to observe that :

$$S_Z = T_Z + B_Z A_Z^{-1} B_Z = \underbrace{T_Z + K_Z}_{\text{Approx.}} -2\omega_{\text{exp}}^2 M_Z + \omega_{\text{exp}}^4 M_Z K_Z^{-1} M_Z$$

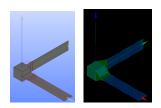
ightharpoonup Applying these approximations, we get the preconditioner P_2 :

$$P_2^{-1} \equiv \left[\begin{array}{ccc} -L_A^{-T}L_A^{-1} & L_A^{-T}L_A^{-1}B_Z \\ 0 & \mathbb{I}_{n-m} \end{array} \right] \left[\begin{array}{ccc} \mathbb{I}_{n-m} & 0 \\ L_S^{-T}L_S^{-1}B_ZD^{-1} & L_S^{-T}L_S^{-1} \end{array} \right]$$



Numerical results

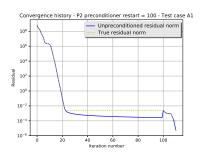
- ▶ We use Petsc (block user implementation) to solve the above linear system. We apply Flexible GMRES method with this setting : restart = depends on each preconditioner, maximum iterations = 10.000, seeked precision = 1e-05.
- Academic application : A three-beam structure.

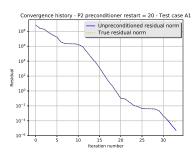






• FGMRES parameters : restart parameter







• Benchmark of direct Cholesky preconditioner

Matrix A_Z	Cholesky direct solve using different packages and ordering methods								
Size = $9,201$		PCSetUP			PCApply	KSPSolve			
$N_{nz} = 602,603$	Ordering	MatGetOrdering	${ m MatCholFctrSym}$	MatCholFctrNum	Total	PCApply	PCSetUP + PCApply	Fill-in	Fill Ratio
PETSc	None	0.00	49.01	27.70	76.70	0.03	76.73	16,980,101	28.17
	ND	0.00	1.00	0.48	1.49	0.00	1.49	1,943,372	3.22
	1WD	0.00	7.04	3.25	10.31	0.01	10.32	5,646,066	9.36
	RCM	0.00	5.42	3.20	8.63	0.01	8.64	5,718,474	9.48
	QMD	0.06	1.01	0.45	1.53	0.00	1.54	1,951,034	3.23
	AMD	0.00	0.91	0.42	1.34	0.00	1.35	1,856,094	3.08
MUMPS	AMD	0.00	0.06	0.34	0.41	0.00	0.42	1,920,557	3.18
	AMF	0.00	0.09	0.56	0.65	0.01	0.66	2,215,053	3.67
	METIS	0.00	0.14	0.40	0.55	0.01	0.56	1,871,817	3.10
	PORD	0.00	0.14	0.47	0.61	0.01	0.62	1,944,021	3.22
	QAMD	0.00	0.09	0.51	0.60	0.01	0.61	2,040,667	3.38
	SCOTCH	0.00	0.20	0.41	0.61	0.01	0.62	1,918,287	3.18





• Nullspace projection test

		Test cases & their null space projection										
Matrix 4	Physical dofs (n)	Lagrange dofs (m)	System size	System nnz	The constraint matrix C	The nullspace basis Z	CPU Time (sec)	Reduced system size	Reduced system nnz			
A_1	10,074	873	21,894	1,798,539		$\begin{array}{ c c c c c }\hline 10,074 \times 9,201 \\ nnz = 12,890 \\\hline \end{array}$	1.3e-2	18,402	1,943,373			
A_2	13,497	1,089	29,172	2,503,134		$ \begin{vmatrix} 13,497 \times 12,408 \\ nnz = 16,977 \end{vmatrix}$	2.9e-2	24,816	2,751,990			
A_3	1,593	22,791	48,768	4,490,766			6.4e-2	42,396	5,071,433			
A_4	64,506	3,273	135,558	13,778,775		$ \begin{vmatrix} 64,506 \times 61233 \\ nnz = 74,794 \end{vmatrix}$	18.8e-2	122,466	16,358,756			





• Parallel test for P₂

Test case	A_4	A_4 Functions & CPU time (sec)					Statistics			
PCSetUP PCApply										
The preconditioner			KSPSolve_Low	KSPSolve_0	KSPSolve_Shur	Total	CPU Time (sec)	Iterations	Flops	True residual
P_2 1 proc	Time (sec) percent (%) Count	311.48 84 3	255.19 69 37	23.25 6 37	89.47 24 37	368.40 99 37	3.716e+02	37	4.490e+09	9.536e-05
P_2 4 procs	Time (sec) percent (%) Count	41.04 61 3	$\begin{array}{ c c c }\hline 40.65 \\ 60 \\ 52 \\ \end{array}$	10.36 15 52	$\begin{vmatrix} 13.47 \\ 20 \\ 52 \end{vmatrix}$	64.79 96 52	6.733e+01	52	2.772e+09	9.531e-05





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Conclusions and perspectives

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Some perspectives

- Application to industrial structures
- ► Need to interface different implementations to be used within the mechanical code CodeAster [®]



