

## Numerical solution of eigenvalue problems from acoustic field computations

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$\triangleright$ Introduction.
$\triangleright$ Application.
$\triangleright$ Linear system.
$\triangleright$ Eigenvalue problems.
$\triangleright$ Future challenges.
$\triangleright$ Conclusions.
$\triangleright$ A cry for help.

## Nonlinear eigenvalue problems in acoustics

The analysis of the acoustic behavior of structures and vehicles needs the numerical solution of parameter dependent linear systems and eigenvalue problems.
$\triangleright$ Such systems have been solved for decades!
$\triangleright$ The mathematics is well-known and used in industrial engineering every day!
$\triangleright$ Numerical methods are available in (commercial) software! (NASTRAN)
$\triangleright$ Do we still need to talk about it?
$\triangleright$ Do we need improved numerical methods?
$\triangleright$ Is the achieved accuracy acceptable?
$\triangleright$ What are the challenges?

## Optimality through mathematics

$\triangleright$ Society is increasingly sensitive to inconveniences that come with modern technologies such as air and water pollution, noise by airplanes, cars, trains.
$\triangleright$ There is an increasing demand for optimal solutions. Minimal energy consumption, minimal noise, pollution, waste.
$\triangleright$ Optimal solutions are obtained by using mathematical techniques, such as model based optimization/ optimal control.
$\triangleright$ We need better mathematical models, faster and more accurate numerical methods, robust implementations on modern computer architectures.
$\triangleright$ Industrial problems create interesting new mathematical problems.
$\triangleright$ Discretization methods, optimization methods and numerical linear algebra methods must go hand in hand.

## Acoustic field in car interior

Project with company SFE in Berlin 2007/2008.
$\triangleright$ Computation of acoustic field for coupled system of car body and air.
$\triangleright$ Use of SFEs parameterized FEM model which allows geometry and topology changes.
$\triangleright$ Frequent solution of linear systems and eigenvalue problems (up to size $10,000,000$ ) within optimization loop that changes geometry, topology, damping material, etc.
$\triangleright$ Ultimate goal: Minimize noise in important regions in car interior.
$\triangleright$ Numerical methods for large scale structured parameter dependent linear systems.
$\triangleright$ These methods are used to determine the frequency response of the system under excitations.
$\triangleright$ Numerical methods for large scale structured parameter dependent nonlinear eigenvalue problems (model reduction for coupled model), modal analysis, optimization of frequencies.
$\triangleright$ Determine all eigenvalues in a given region of $\mathbb{C}$.
$\triangleright$ Determine projectors on important spectral subspaces for model reduction.
$\triangleright$ Implementation of parallel solver in SFE Concept.

## Frequency response I



## Frequency response II



## Mathematical model: Linear system

Solve $P(\omega, \alpha) u(\omega, \alpha)=f(\omega, \alpha)$, where

$$
P(\omega, \alpha):=-\omega^{2}\left[\begin{array}{cc}
M_{s} & 0 \\
0 & M_{f}
\end{array}\right]+\imath \omega\left[\begin{array}{cc}
D_{s} & D_{a s}^{T} \\
D_{a s} & D_{f}
\end{array}\right]+\left[\begin{array}{cc}
K_{s}(\omega) & 0 \\
0 & K_{f}
\end{array}\right],
$$

is complex symmetric of dimension up to $10,000,000$,
$\triangleright M_{s}, M_{f}, K_{f}$ are real symm. pos. semidef. mass/stiffness matrices of structure and air, $M_{s}$ is singular and diagonal, $M_{f}$ is sparse. $M_{s}$ is a factor $1000-10000$ larger than $M_{f}$.
$\triangleright K_{s}(\omega)=K_{s}(\omega)^{T}=K_{1}(\omega)+\imath K_{2}$.
$\triangleright D_{s}$ is a real damping matrix, $D_{f}$ is complex symmetric.
$\triangleright D_{a s}$ is real coupling matrix between structure and air.
$\triangleright$ All or part of the matrices depend on geometry, topology and material parameters.

## Sparsity of fluid mass matrix $M_{t}$




## Sparsity of $K_{2}$



## Detailed tasks

$\triangleright$ Solve for a given set of parameters $\alpha_{i}, i=1,2, \ldots$, the linear system $P(\omega) u(\omega)=f(\omega)$, for $\omega=0, \ldots, 1000 h z$ in small frequency steps.
$\triangleright$ The parameters $\alpha_{i}$ are determined in a manual or (later) automatic optimization process, i.e. $\alpha_{i}$ and $\alpha_{i+1}$ are close.
$\triangleright$ Parallelization in multi-processor multicore environment.
$\triangleright$ Often many right hand sides (load vectors) $f(\omega)$.
$\triangleright$ Accuracy goal: Relative residual $10^{-6}$.

## Difficulties and challenges

$\triangleright$ Problems are badly scaled and get increasingly ill-conditioned when $\omega$ grows.
$\triangleright$ For some parameter constellations the system becomes exactly singular with inconsistent right hand side.
$\triangleright$ Direct solution methods would be ideal but work only work out-of-core.
$\triangleright$ Small blocks of matrices are changed with $\alpha$ remaining system is the same.
$\triangleright$ No multilevel or adaptive grid refinement available, methods must be purely matrix based.

## Our contribution

$\triangleright$ Generated and implemented subspace recycling Krylov subspace method with sparse out of core $L D L^{\top}$ preconditioner (MUMPS, PARDISO) for real part of linear system, i.e.

$$
\tilde{P}(\omega):=-\omega^{2}\left[\begin{array}{cc}
M_{s} & 0 \\
0 & M_{f}
\end{array}\right]+\left[\begin{array}{cc}
K_{1} & 0 \\
0 & K_{f}
\end{array}\right] .
$$

$\triangleright$ For small $\omega$ only 2 - 4 iteration steps per frequency are necessary.
$\triangleright$ The number of iteration steps grows substantially for larger $\omega$ so that more and more new preconditioners are needed or the number of iterations or restarts increases.

## Comparison with NASTRAN




Consider nonlinear eigenvalue problem $P(\lambda) x=0$, where the matrix polynomial

$$
P(\lambda):=\lambda^{2}\left[\begin{array}{cc}
M_{s} & 0 \\
0 & M_{f}
\end{array}\right]+\lambda\left[\begin{array}{cc}
D_{s} & D_{a s}^{T} \\
D_{a s} & D_{f}
\end{array}\right]+\left[\begin{array}{cc}
K_{s}(\lambda) & 0 \\
0 & K_{f}
\end{array}\right],
$$

is complex symmetric and has dimension up to 10,000,000, and all coefficients depend in part on $\alpha$.
$\triangleright$ Compute all smallest real eigenvalues in a given region of $\mathbb{C}$ and associated eigenvectors.
$\triangleright$ Project the problem into the subspace spanned by these eigenvectors.
$\triangleright$ Solve the second order differential algebraic system (DAE).
$\triangleright$ Optimize the eigenfrequencies/acoustic field w.r.t. the set of parameters.

## Numerical methods for polynomial eigenvalue problems

Methods directly for nonlinear problem (incomplete list). For surveys see M./Voss 2005 or Dissertation Schreiber 2008.
$\triangleright$ Second order Arnoldi method Bai 2006
$\triangleright$ Rational Krylov method Ruhe 1998, 2000
$\triangleright$ Residual iteration method Neumaier 1985
$\triangleright$ Newton-Type methods Schreiber/Schwetlick 2006, 2008,
$\triangleright$ Rayleigh quotient iterations Schreiber 2008, Freitag/Spence 2007, 2008
$\triangleright$ Jacobi-Davidson method Sleijpen/Van der Vorst et al 1996, Betcke/Voss 2004, Hochstenbach 2007
$\triangleright$ Arnoldi type methods Voss 2003

## Can we use these methods

$\triangleright$ None of these methods can be applied directly.
$\triangleright$ We need to improve convergence and preconditioning.
$\triangleright$ We need better perturbation and error analysis.
$\triangleright$ How can we guarantee a required accuracy.
$\triangleright$ We need the methods in parallel on modern multi-processor, multi-core machines.

## Challenges

$\triangleright$ Guarantee that all desired eigenvalues are obtained.
$\triangleright$ Guaranteed relative residual?
$\triangleright$ Previously used decoupled methods for structure/fluid subsystems do not work appropriately.
$\triangleright$ Problem is in some cases truely nonlinear since $K_{s}$ may depend on $\lambda$.
$\triangleright$ Eigenvalue is very ill-conditioned for some parameter sets.
$\triangleright$ Mass matrix is block diagonal and singular. (Nullspace is available without extra computation.)
$\triangleright$ Infinite eigenvalues have index 2.
$\triangleright$ For some parameters $\alpha$ the whole matrix polynomial is singular.
$\triangleright$ Locking and purging or deflation of converged eigenvalues?

## Our contribution so far

$\triangleright$ Analysis of singularity and structure.
$\triangleright$ Trimmed structured linearization method to deal with singular mass matrix and singular pencil. Byers/M./Xu 2007
$\triangleright$ Implicitly restarted Arnoldi for undamped system with guaranteed eigenvalues in a given interval for undamped systems. This is used as starting configuration in homotopy method for damped system. (Diploma thesis Elena Teidelt 2008)
$\triangleright$ Newton-like methods and generalized Rayleigh quotient methods for general nonlinear systems (Dissertation Kathrin Schreiber May 2008)
$\triangleright$ Special deflation methods for converged eigenvalues.

## Linearization

The classical companion linearization for polynomial eigenvalue problems

$$
P(\lambda) x=\sum_{i=0}^{k} \lambda^{i} \boldsymbol{A}_{i} x
$$

is to introduce new variables

$$
T=\left[y_{1}, y_{2}, \ldots, y_{k}\right]^{T}=\left[x, \lambda x, \ldots, \lambda^{k-1} x\right]^{T}
$$

and to turn it into a generalized linear eigenvalue problem

$$
L(\lambda) y:=(\lambda \mathcal{E}+\mathcal{A}) y=0
$$

of size $n k \times n k$.

## Linearization

Definition: For a matrix polynomial $P(\lambda)$ of degree $k$, a matrix pencil $L(\lambda)=(\lambda \mathcal{E}+\mathcal{A})$ is called linearization of $P(\lambda)$, if there exist nonsingular unimodular matrices (i.e., of constant nonzero determinant) $S(\lambda), T(\lambda)$ such that

$$
S(\lambda) L(\lambda) T(\lambda)=\operatorname{diag}\left(P(\lambda), I_{(n-1) k}\right) .
$$

## Properties of companion linearization

$\triangleright$ Companion linearization preserves the algebraic and geometric multiplicities of all finite eigenvalues.
$\triangleright$ There are some difficulties with multiple eigenvalues including $\infty$ and the singular part, Byers/M./Xu 2008.
$\triangleright$ The geometric multiplicity of the eigenvalue $\infty$ and the sizes of singular blocks are not invariant under unimodular transformations.
$\triangleright$ Companion linearization destroys the structure.

## Example: Constrained Multi-body system

Consider the Euler-Lagrange equations of a linear,

$$
\begin{aligned}
\hat{M} \ddot{x}+\hat{D} \dot{x}+\hat{K} x+\hat{G}^{T} \mu & =f(t) \\
\hat{G} x & =g .
\end{aligned}
$$

The associated matrix polynomial is

$$
P(\lambda)=\lambda^{2}\left[\begin{array}{cc}
\hat{M} & 0 \\
0 & 0
\end{array}\right]+\lambda\left[\begin{array}{ll}
\hat{D} & 0 \\
0 & 0
\end{array}\right]+\left[\begin{array}{cc}
\hat{K} & \hat{G}^{T} \\
\hat{G} & 0
\end{array}\right] .
$$

If $\hat{M}$ is positive definite and $\hat{G}$ has full row rank, then the companion form has a Kronecker block associated with $\infty$ of size 4.

## Modified first order form

The first order formulation used in multibody dynamics only introduces $\boldsymbol{y}=\dot{\boldsymbol{x}}$ and not $\gamma=\dot{\mu}$.

$$
\begin{aligned}
M \dot{y}+D \dot{x}+K x+G^{T} \mu & =f(t), \\
\dot{x} & =y, \\
G x & =0
\end{aligned}
$$

and the associated linear matrix pencil

$$
\tilde{L}(\lambda)=\lambda\left[\begin{array}{lll}
M & 0 & 0 \\
0 & l & 0 \\
0 & 0 & 0
\end{array}\right]+\left[\begin{array}{ccc}
D & K & G^{T} \\
-I & 0 & 0 \\
0 & G & 0
\end{array}\right],
$$

has a Kronecker block at $\infty$ of size 3 . Even smaller blocks can be achieved.

## Companion form and structure

Example For the complex symmetric problem

$$
\left(\lambda^{2} M+\lambda D+K\right) x=0
$$

the companion linearizations

$$
\lambda\left[\begin{array}{cc}
1 & O \\
O & M
\end{array}\right]-\left[\begin{array}{cc}
O & 1 \\
K & -D
\end{array}\right], \quad \lambda\left[\begin{array}{cc}
1 & O \\
D & M
\end{array}\right]-\left[\begin{array}{cc}
O & 1 \\
K & O
\end{array}\right]
$$

do not preserve the structure and the symmetric versions

$$
\lambda\left[\begin{array}{cc}
K & O \\
O & M
\end{array}\right]-\left[\begin{array}{cc}
O & K \\
K & -D
\end{array}\right], \quad \lambda\left[\begin{array}{cc}
M & O \\
D & M
\end{array}\right]-\left[\begin{array}{cc}
O & M \\
K & O
\end{array}\right]
$$

may be singular. Linearization theory Mackey/Mackey/Mehl/M. 2006, Mackey/Higham/Tisseur 2006, Dopico/Mackey/Teran 2008 is needed.

## Trimmed linearization

Consider the polynomial eigenvalue problem

$$
\left(\sum_{i=0}^{k} A_{i} \lambda^{i}\right) x=0 .
$$

$\triangleright$ Can we do as in the multibody context?
$\triangleright$ Can we remove singular and high index parts for the eigenvalue $\infty$ completely.
$\triangleright$ In Byers/M./Xu 2008 a new trimmed linearization theory is developed.

## A simple example

Consider the DAE

$$
\left[\begin{array}{ll}
1 & 0 \\
0 & 0
\end{array}\right]\left[\begin{array}{l}
\ddot{x} \\
\ddot{\mu}
\end{array}\right]+\left[\begin{array}{ll}
1 & 0 \\
0 & 0
\end{array}\right]\left[\begin{array}{l}
\dot{x} \\
\dot{\mu}
\end{array}\right]+\left[\begin{array}{ll}
1 & 1 \\
1 & 0
\end{array}\right]\left[\begin{array}{l}
x \\
\mu
\end{array}\right]=\left[\begin{array}{l}
f_{1} \\
f_{2}
\end{array}\right] .
$$

Index reduction (inserting the derivatives of the second equation into the first) gives the first order DAE

$$
\left[\begin{array}{ll}
0 & 1 \\
1 & 0
\end{array}\right]\left[\begin{array}{l}
x \\
\mu
\end{array}\right]=\left[\begin{array}{c}
f_{1}-f_{2}-\dot{f}_{2}-\ddot{f}_{2} \\
f_{2}
\end{array}\right] .
$$

This is first order, no first order formulation is necessary.

## The associated matrix polynomial

$$
P(\lambda)=\left[\begin{array}{cc}
\lambda^{2}+\lambda+1 & 1 \\
1 & 0
\end{array}\right]
$$

has only the eigenvalue $\infty$. Using a unimodular transformation from the left with

$$
Q(\lambda)=\left[\begin{array}{cc}
1 & -\left(\lambda^{2}+\lambda+1\right) \\
0 & 1
\end{array}\right]
$$

we obtain the first order

$$
T(\lambda)=Q(\lambda) P(\lambda)=\left[\begin{array}{ll}
0 & 1 \\
1 & 0
\end{array}\right]
$$

which has only degree 0 .
Is this a polynomial of degree 2 , or 1 with leading coefficients 0 .

Theorem Byers/M./Xu 2007
Let $A_{i} \in \mathbb{C}^{m, n} i=0, \ldots, k$. Then, the tuple $\left(A_{k}, \ldots, A_{0}\right)$ is unitarily equivalent to a matrix tuple $\left(\hat{A}_{k}, \ldots, \hat{A}_{0}\right)=\left(U A_{k} V, \ldots, U A_{0} V\right)$, where all terms $\hat{A}_{i}, i=0, \ldots, k$, have the form


## Properties of this staircase form

$\triangleright$ Each of the blocks $A_{j}^{(i)} i=0, \ldots, k, j=1, \ldots, l$ either has the form $\left[\begin{array}{ll}\Sigma & 0\end{array}\right]$ or $\left[\begin{array}{ll}0 & 0\end{array}\right]$,
$\triangleright$ Each of the blocks $\tilde{A}_{j}^{(i)} i=1, \ldots, k, j=1, \ldots, l$ either has the form $\left[\begin{array}{l}\Sigma \\ 0\end{array}\right]$ or $\left[\begin{array}{l}0 \\ 0\end{array}\right]$.
$\triangleright$ For each $j$ only one of the $A_{j}^{(i)}$ and $\tilde{A}_{j}^{(i)}$ is nonzero.
$\triangleright$ In the tuple of middle blocks $\left(A_{0}^{(k)}, \ldots, A_{0}^{(k)}\right)$ no $k$ of the coefficients have a common nullspace.
$\triangleright$ Is this all we need?

## Deflation of singular parts

Let $P(\lambda) x(\lambda) \equiv 0, \tilde{x}(\lambda):=V x(\lambda)$, where $V$ is as in staircase form, and set

$$
\left[\begin{array}{ccc}
P_{11}(\lambda) & P_{12}(\lambda) & P_{13}(\lambda) \\
P_{21}(\lambda) & P_{22}(\lambda) & 0 \\
P_{31}(\lambda) & 0 & 0
\end{array}\right]\left[\begin{array}{c}
x_{1}(\lambda) \\
x_{2}(\lambda) \\
x_{3}(\lambda)
\end{array}\right]=0 .
$$

Then $x_{1}(\lambda) \equiv 0$, i.e. the right singular blocks of the polynomial $P(\lambda)$ are contained in the submatrix polynomial
$\left.\begin{array}{cc}P_{12}(\lambda) & P_{13}(\lambda) \\ P_{22}(\lambda) & 0\end{array}\right]$.
All the eigenvalue information associated with finite nonzero eigenvalues is contained in $P_{22}(\lambda)$.

## Properties of staircase form

$\triangleright$ Staircase form allows to deflate long chains associated with $\infty$ and singular part.
$\triangleright$ Concept can be extended to any other eigenvalue.
$\triangleright$ Unfortunately for degree $>1$ the information may not be complete, see following example.
$\triangleright$ There is a good case, where all the information is available.

## Bad Example

$$
P(\lambda)=\lambda^{2}\left[\begin{array}{ll}
1 & 0 \\
0 & 0
\end{array}\right]+\lambda\left[\begin{array}{ll}
0 & 1 \\
1 & 0
\end{array}\right]+\left[\begin{array}{ll}
0 & 0 \\
0 & 2
\end{array}\right],
$$

has double eigenvalues at $0, \infty$ with right and left chains

$$
x_{1}=\left[\begin{array}{l}
0 \\
1
\end{array}\right], \quad x_{2}=\left[\begin{array}{r}
-1 \\
0
\end{array}\right]
$$

associated with infinity and

$$
z_{1}=\left[\begin{array}{l}
1 \\
0
\end{array}\right], \quad z_{2}=\left[\begin{array}{c}
0 \\
-1 / 2
\end{array}\right]
$$

associated with 0 . No two coefficients have a common nullspace.
We cannot reduce this matrix polynomial further with strong equivalence.

## Complete information about ev. $0, \infty$.

The complete information associated with $0, \infty$ is available if the staircase procedure ends up with a tuple of middle blocks $\left(A_{0}^{(k)}, \ldots, A_{0}^{(k)}\right)$ which has a growing anti-triangular form

$$
\begin{aligned}
& \left(\left[\begin{array}{ccccc}
\Sigma_{k} & 0 & \cdots & 0 & 0 \\
0 & 0 & \cdots & 0 & 0 \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
0 & \cdots & \cdots & \cdots & 0
\end{array}\right],\left[\begin{array}{ccccc}
A_{11}^{(k-1)} & A_{12}^{(k-1)} & 0 & \cdots & 0 \\
A_{21}^{(k-1)} & \Sigma_{k-1} & 0 & \cdots & 0 \\
0 & 0 & 0 & \cdots & \vdots \\
\vdots & \vdots & \vdots & \ddots & 0 \\
0 & 0 & \cdots & \cdots & 0
\end{array}\right]\right. \\
& \left.\left[\begin{array}{ccccc}
A_{11}^{(1)} & A_{12}^{(1)} & \ldots & A_{1, k-1}^{(1)} & 0 \\
\vdots & \ddots & \ldots & A_{2, k-1}^{(1)} & 0 \\
\vdots & \vdots & \ddots & \ldots & \vdots \\
A_{k-1,1}^{(1)} & A_{k-1,2}^{(1)} & \cdots & \Sigma_{1} & 0 \\
0 & 0 & 0 & 0
\end{array}\right],\left[\begin{array}{ccccc}
A_{11}^{(0)} & A_{12}^{(0)} & \cdots & \cdots & A_{1, k}^{(0)} \\
\vdots & \ddots & \cdots & \cdots & A_{2, k}^{(0)} \\
\vdots & \vdots & \ddots & & \vdots \\
A_{k-1,1}^{(0)} & A_{k-1,2}^{(0)} & \cdots & A_{k-1, k-1}^{(0)} & A_{k-1, k}^{(0)} \\
A_{k, 1}^{(0)} & A_{k, 2}^{(0)} & \cdots & A_{k, k-1}^{(0)} & \Sigma_{0}
\end{array}\right]\right)
\end{aligned}
$$

Corollary If the middle block has growing anti-triangular form and is regular, then it only has simply eigenvalues associated with $\infty$.
Consider the associated eigenvalue problem $P_{22}(\lambda) \tilde{x}=0$ with $\tilde{x}=\left[x_{0}^{T}, x_{1}^{\top}, \ldots, x_{k}^{T}\right]^{T}$. Then we obtain a linear eigenvalue problem by introducing selected new variables (different from the usual companion form). Let

$$
\begin{aligned}
& z_{0,1}=\lambda x_{0}, \quad z_{0,2}=\lambda z_{0,1}=\lambda^{2} x_{0}, \ldots, z_{0, k-1}=\lambda z_{0, k-2}=\lambda^{k-1} x_{0}, \\
& z_{1,1}=\lambda x_{1}, \quad z_{1,2}=\lambda z_{1,1}=\lambda^{2} x_{1}, \ldots, z_{1, k-2}=\lambda z_{1, k-3}=\lambda^{k-2} x_{1}, \\
& \vdots \\
& z_{k-2,1}=\lambda x_{k-2} .
\end{aligned}
$$

Define
$z=\left[x_{0}^{T}, x_{1}^{T}, \ldots, x_{k}^{T}, z_{0,1}^{T}, \ldots, z_{k-2,1}^{T}, z_{0,2}^{T}, \ldots, z_{k-3,2}^{T}, \ldots, z_{0, k-2}^{T}, z_{1, k-2}^{T}, z_{0, k}^{T}\right.$
We call this trimmed linearization.

## What do we learn from this?

$\triangleright$ The trimmed linearization theory allows to remove singular parts and high index parts directly in the nonlinear system.
$\triangleright$ In our application we can apply this technique directly to get regular structured linearizations.
$\triangleright$ No null-space computation is necessary, since the kernel of $M$ is available directly and exactly.
$\triangleright$ Thus we can use structured methods for generalized eigenvalue problems.

## Finding all evs in an interval/box

One of the goals is to find all eigenvalues in a real interval $[a, b]$ (undamped case) or a box of the complex plane.
$\triangleright$ This is relatively easy for the undamped problem $\lambda^{2} M-K$, we need to find all eigenvalues in a given real interval $[a, b]$.
$\triangleright$ Carry out factorizations $P(a)=L(a) D(a) L(a)^{T}$ and $P(b)=L(b) D(b) L(b)^{T}$ and use inertia to determine number of eigenvalues in interval.
$\triangleright$ Use several starts of implicitly restarted Arnoldi with shift-and-invert preconditioner for $P(a)^{-1}, P(b)^{-1}$, $P((b-a) / 2)^{-1}, \ldots$ until all eigenvalues are found.
$\triangleright$ In the general case we can use Bendixon's theorem or Gersgorin type results to analyse the number of eigenvalues.
$\triangleright$ The computation can be done as in the interval case with several complex targets or using the sign function method.

## Numerical results I, Dipl.

$\triangleright$ Balanced, scaled problem, infinite eigenvalues deflated.
$\triangleright$ Matrix dimension: 478788 . Smallest 50 eigenvalues
$\triangleright$ Condition number kappa $=\left||x|^{2} /|\operatorname{lambda}|^{2} *\right| x^{\prime} * M * x \mid$
$\triangleright 1$ factorization needed.

| Ev. no | $\lambda$ | residual | $\kappa$ |
| :---: | :---: | :---: | :---: |
| 1 | $3.116828 e+01$ | $2.784910 e-16$ | $1.381088 e+08$ |
| 2 | $3.939059 e+01$ | $2.632970 e-16$ | $7.76505 e+07$ |
| 3 | $4.770588 e+01$ | $2.730574 e-16$ | $6.185278 e+07$ |
| $\vdots$ | $\vdots$ | $\vdots$ | $\vdots$ |
| 6 | $6.553705 e+01$ | $2.687169 e-16$ | $3.215041 e+07$ |
| 7 | $1.435197 e+02$ | $2.508269 e-16$ | $6.759916 e+06$ |
| $\vdots$ | $\vdots$ | $\vdots$ | $\vdots$ |
| 48 | $6.600993 e+02$ | $1.716196 e-16$ | $3.239416 e+05$ |
| 49 | $6.677409 e+02$ | $3.189563 e-16$ | $5.416045 e+05$ |
| 50 | $6.837248 e+02$ | $2.204968 e-13$ | $4.647000 e+05$ |

## Numerical results II Dipl.

$\triangleright$ Balanced, scaled problem, infinite eigenvalue deflated.
$\triangleright$ Matrix dimension: 478788
$\triangleright$ All eigenvalues in $[400,650]$
$\triangleright 31$ eigenvalues found, all converged.
$\triangleright 2$ factorizations needed.

| Ev. no | $\lambda$ | residual | $\kappa$ |
| :---: | :---: | :---: | :---: |
| 1 | $4.007569 e+02$ | $5.566134 e-16$ | $1.747769 e+06$ |
| $\vdots$ | $\vdots$ | $\vdots$ | $\vdots$ |
| 30 | $6.427129 e+02$ | $1.286406 e-08$ | $2.231207 e+05$ |
| 31 | $6.431337 e+02$ | $1.149491 e-08$ | $2.423338 e+05$ |

## General quadratic problem, in progress

$\triangleright$ Bring in damping via homotopy. Solve

$$
\left(1-t_{i}\right)\left(\lambda^{2} M+K\right)+t_{i}(\lambda D), t_{0}, \ldots, t_{\ell} \in[0,1]
$$

$\triangleright$ Use computed symmetric factorizations as long as possible.
$\triangleright$ Use new symmetric factorizations of real part.
$\triangleright$ Recycle Krylov subspaces when possible.
$\triangleright$ Follow eigenvalue curves with stepsize control to guarantee that no eigenvalue is missed.
$\triangleright$ Use Newton method for fully nonlinear problem.

## Nonlinear Newton evp. solver.

Truely nonlinear evp $T(\lambda) x=\left(\lambda^{2} M+\lambda D+K(\lambda)\right) x=0$. Apply Newton to function

$$
f_{w}(x, \lambda)=\left[\begin{array}{c}
T(\lambda) x \\
w^{H} x-1
\end{array}\right]=0 .
$$

The Newton system for $\lambda_{k+1}=\lambda_{k}+\mu_{k}$ and $x_{k+1}=x_{k}+s_{k}$ is

$$
\left[\begin{array}{cc}
T\left(\lambda_{k}\right) & \dot{T}\left(\lambda_{k}\right) x_{k} \\
w^{H} & 0
\end{array}\right]\left[\begin{array}{c}
s_{k} \\
\mu_{k}
\end{array}\right]=-\left[\begin{array}{c}
T\left(\lambda_{k}\right) x_{k} \\
w^{H} x_{k}-1
\end{array}\right]
$$

or

$$
\begin{aligned}
& \lambda_{k+1}=\lambda_{k}-\frac{1}{w^{H} T\left(\lambda_{k}\right)^{-1} \dot{T}\left(\lambda_{k}\right) x_{k}} \\
& x_{k+1}=\left(\lambda_{k}-\lambda_{k+1}\right) T\left(\lambda_{k}\right)^{-1} \dot{T}\left(\lambda_{k}\right) x_{k} .
\end{aligned}
$$

## Dissertation

$\triangleright$ Conditions for local quadratic convergence of Newton.
$\triangleright$ Proof of local cubic connvergence of two-sided nonlinear Jacobi-Davidson and Rayleigh quotient interation.
$\triangleright$ Implementation of method.
$\triangleright$ Comparison of methods Newton type, Jacobi Davidson, nonlinear two-sided Rayleigh quotients.
$\triangleright$ Special methods for complex symmetric problems.

## Difficulties

$\triangleright$ Small homotopy steps necessary to track eigenvalues of polynomial and nonlinear problem.
$\triangleright$ Need to store intermediate Krylov subspaces to make efficient restart.
$\triangleright$ Need to use out-of-core sparse solvers.
$\triangleright$ Need to get into convergence intervals for Newton, JD.
$\triangleright$ No global analysis and industrial implementation yet.

## Model/modal reduction

$\triangleright$ After desired eigenvalues and corresponding deflating subspaces $U=\left[u_{1}, \ldots, k\right]$ have been computed, the projected coupled DAE system

$$
U^{\top} M(\alpha) U \ddot{z}+U^{\top} D(\alpha) U \dot{z}+U^{\top} K(\alpha) U z=U^{\top} f
$$

is formed and eigenvalue/frequency optimization is done on this system.
$\triangleright$ The decoupled projection does not work.
$\triangleright$ We would really need nonlinear model reduction.
$\triangleright$ We need to use the fact that only a small part of the system is changed in every optimization step.
$\triangleright$ We need to integrate ev computation, gradient computation, discretization.
$\triangleright$ A multilevel approach would be great.

## Conclusions

$\triangleright$ Industrial applications lead to nice mathematical questions.
$\triangleright$ Commercially available codes are not satisfactory.
$\triangleright$ Coupled nonlinear eigenvalue with a structured part.
$\triangleright$ Structure preserving linearization techniques have been derived for polynomial part, but infinite eigenvalues and singularities need to be deflated first.
$\triangleright$ Homotopy and Newton like method are developed.
$\triangleright$ Industrial production code development is a challenge.

## Acry for help.

$\triangleright$ Really nonlinear eigenvalue solvers are not well understood.
$\triangleright$ Conditioning and accuracy of eigenvalues is not well understood.
$\triangleright$ Jacobi-Davidson method need to be improved to be compatible.
$\triangleright$ Deflation of converged eigenvalues need to be improved.
$\triangleright$ Subspace recycling in homotopy, Newton, and optimization methods needs to be improved.
$\triangleright$ Linear system and eigenvalue solvers need to be better adapted.
$\triangleright$ Adaptive methods for PDE eigenvalue problems are needed.

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Thank you very much for your attention.

