

A new approach to flexible preconditioning for the iterative solution of the time-harmonic elastic wave equation at multiple frequencies

M. Baumann^{*,†} and M. B. van Gijzen[†]

*Email: M.M.Baumann@tudelft.nl

[†]Delft Institute of Applied Mathematics
Delft University of Technology
Delft, the Netherlands

Progress meeting, October 25, 2013

Table of contents

- 1 Model problem
- 2 Krylov methods for shifted linear systems
- 3 The shift-and-invert preconditioner
- 4 FOM preconditioning for flexible Krylov methods
- 5 First numerical results
- 6 Discussion and Outlook

The time-harmonic elastic wave equation

For many frequencies ω_k , $k = 1, \dots, N$, we consider

$$\begin{aligned} -\mu \Delta \mathbf{u} - (\mu + \lambda) \nabla (\nabla \cdot \mathbf{u}) - \omega_k^2 \rho_s \mathbf{u} &= \mathbf{r}, \quad \text{in } \Omega \subset \mathbb{R}^D, \\ i\gamma \omega_k \rho_s B \mathbf{u} + [\lambda (\nabla \cdot \mathbf{u}) + \mu (\nabla \mathbf{u} + (\nabla \mathbf{u})^T)] \mathbf{n} &= 0, \quad \text{on } \partial\Omega, \end{aligned}$$

where

Assumptions

- $\mathbf{u} \in \mathbb{R}^D$ is the displacement vector in two ($D = 2$) or three ($D = 3$) dimensions,
- $\mu, \lambda \in \mathbb{R}$ are the so-called Lamé parameters,
- $\rho_s \in \mathbb{R}$ is the (constant) material density,
- $B \in \mathbb{R}^{D \times D}$ is defined componentwise, $B_{ij} \equiv c_p n_i n_j + c_s t_i t_j$, for $D = 2$.

The time-harmonic elastic wave equation

For many frequencies ω_k , $k = 1, \dots, N$, we consider

$$\begin{aligned} -\mu \Delta \mathbf{u} - (\mu + \lambda) \nabla (\nabla \cdot \mathbf{u}) - \omega_k^2 \rho_s \mathbf{u} &= \mathbf{r}, \quad \text{in } \Omega \subset \mathbb{R}^D, \\ i\gamma \omega_k \rho_s B \mathbf{u} + [\lambda (\nabla \cdot \mathbf{u}) + \mu (\nabla \mathbf{u} + (\nabla \mathbf{u})^T)] \mathbf{n} &= 0, \quad \text{on } \partial\Omega, \end{aligned}$$

where

Assumptions

- $\mathbf{u} \in \mathbb{R}^D$ is the displacement vector in two ($D = 2$) or three ($D = 3$) dimensions,
- $\mu, \lambda \in \mathbb{R}$ are the so-called Lamé parameters,
- $\rho_s \in \mathbb{R}$ is the (constant) material density,
- $B \in \mathbb{R}^{D \times D}$ is defined componentwise, $B_{ij} \equiv c_p n_i n_j + c_s t_i t_j$, for $D = 2$.

The time-harmonic elastic wave equation

For many frequencies ω_k , $k = 1, \dots, N$, we consider

$$\begin{aligned} -\mu \Delta \mathbf{u} - (\mu + \lambda) \nabla (\nabla \cdot \mathbf{u}) - \omega_k^2 \rho_s \mathbf{u} &= \mathbf{r}, \quad \text{in } \Omega \subset \mathbb{R}^D, \\ i\gamma \omega_k \rho_s B \mathbf{u} + [\lambda (\nabla \cdot \mathbf{u}) + \mu (\nabla \mathbf{u} + (\nabla \mathbf{u})^T)] \mathbf{n} &= 0, \quad \text{on } \partial\Omega, \end{aligned}$$

where

Assumptions

- $\mathbf{u} \in \mathbb{R}^D$ is the displacement vector in two ($D = 2$) or three ($D = 3$) dimensions,
- $\mu, \lambda \in \mathbb{R}$ are the so-called Lamé parameters,
- $\rho_s \in \mathbb{R}$ is the (constant) material density,
- $B \in \mathbb{R}^{D \times D}$ is defined componentwise, $B_{ij} \equiv c_p n_i n_j + c_s t_i t_j$, for $D = 2$.

The time-harmonic elastic wave equation

For many frequencies ω_k , $k = 1, \dots, N$, we consider

$$\begin{aligned} -\mu \Delta \mathbf{u} - (\mu + \lambda) \nabla (\nabla \cdot \mathbf{u}) - \omega_k^2 \rho_s \mathbf{u} &= \mathbf{r}, \quad \text{in } \Omega \subset \mathbb{R}^D, \\ i\gamma \omega_k \rho_s B \mathbf{u} + [\lambda (\nabla \cdot \mathbf{u}) + \mu (\nabla \mathbf{u} + (\nabla \mathbf{u})^T)] \mathbf{n} &= 0, \quad \text{on } \partial\Omega, \end{aligned}$$

where

Assumptions

- $\mathbf{u} \in \mathbb{R}^D$ is the displacement vector in two ($D = 2$) or three ($D = 3$) dimensions,
- $\mu, \lambda \in \mathbb{R}$ are the so-called Lamé parameters,
- $\rho_s \in \mathbb{R}$ is the (constant) material density,
- $B \in \mathbb{R}^{D \times D}$ is defined componentwise, $B_{ij} \equiv c_p n_i n_j + c_s t_i t_j$, for $D = 2$.

The time-harmonic elastic wave equation

For many frequencies ω_k , $k = 1, \dots, N$, we consider

$$\begin{aligned} -\mu \Delta \mathbf{u} - (\mu + \lambda) \nabla (\nabla \cdot \mathbf{u}) - \omega_k^2 \rho_s \mathbf{u} &= \mathbf{r}, \quad \text{in } \Omega \subset \mathbb{R}^D, \\ i\gamma \omega_k \rho_s B \mathbf{u} + [\lambda (\nabla \cdot \mathbf{u}) + \mu (\nabla \mathbf{u} + (\nabla \mathbf{u})^T)] \mathbf{n} &= 0, \quad \text{on } \partial\Omega, \end{aligned}$$

where

Assumptions

- $\mathbf{u} \in \mathbb{R}^D$ is the displacement vector in two ($D = 2$) or three ($D = 3$) dimensions,
- $\mu, \lambda \in \mathbb{R}$ are the so-called Lamé parameters,
- $\rho_s \in \mathbb{R}$ is the (constant) material density,
- $B \in \mathbb{R}^{D \times D}$ is defined componentwise, $B_{i,j} \equiv c_p n_i n_j + c_s t_i t_j$, for $D = 2$.

Discretization

using the finite element method (FEM)

After FEM-discretization, we obtain the linear systems

$$(K + i\omega_k C - \omega_k^2 M)\underline{\mathbf{u}} = \underline{\mathbf{r}},$$

with K, C, M being symmetric and sparse.

Re-formulation yields

$$\left[\begin{pmatrix} iM^{-1}C & M^{-1}K \\ I & 0 \end{pmatrix} - \omega_k \begin{pmatrix} I & 0 \\ 0 & I \end{pmatrix} \right] \begin{pmatrix} \omega_k \underline{\mathbf{u}} \\ \underline{\mathbf{u}} \end{pmatrix} = \begin{pmatrix} M^{-1}\underline{\mathbf{r}} \\ 0 \end{pmatrix},$$

which is of the form

$$(A - \omega_k I)\mathbf{x}_k = \mathbf{b}, \quad \omega_k = 1, \dots, N.$$

Krylov methods for shifted linear systems

Main observation

For shifted linear systems

$$(A - \omega I)\mathbf{x} = \mathbf{b}, \quad \omega \in \mathbb{R},$$

the Krylov subspaces are **invariant**, i.e.:

$$\mathcal{K}_m(A, b) \equiv \text{span} \{b, Ab, \dots, A^{m-1}b\} = \mathcal{K}_m(A - \omega I, b).$$

Main advantage:

- Perform Arnoldi algorithm only once, and use:

$$\begin{aligned} AV_m &= V_{m+1} \underline{H}_m \\ \Rightarrow (A - \omega I)V_m &= V_{m+1}(\underline{H}_m - \omega \underline{I}_m) \end{aligned}$$

Krylov methods for shifted linear systems

Main observation

For shifted linear systems

$$(A - \omega I)\mathbf{x} = \mathbf{b}, \quad \omega \in \mathbb{R},$$

the Krylov subspaces are **invariant**, i.e.:

$$\mathcal{K}_m(A, b) \equiv \text{span} \{b, Ab, \dots, A^{m-1}b\} = \mathcal{K}_m(A - \omega I, b).$$

Main advantage:

- Perform Arnoldi algorithm only once, and use:

$$\begin{aligned} AV_m &= V_{m+1} \underline{H}_m \\ \Rightarrow (A - \omega I)V_m &= V_{m+1}(\underline{H}_m - \omega \underline{I}_m) \end{aligned}$$

Krylov methods for shifted linear systems

Preconditioning multishift problems

Main disadvantage:

- Preconditioners are in general not easy to apply. For

$$(A - \omega I)M_{\omega}^{-1}y_{\omega} = b, \quad x_{\omega} = M_{\omega}^{-1}y_{\omega}$$

it does **not** hold:

$$\mathcal{K}_m(AM_{\omega}^{-1}, b) \neq \mathcal{K}_m(AM_{\omega}^{-1} - \omega M_{\omega}^{-1}, b)$$

However, there is a way...

References

- Y. A. Erlangga, *A robust and efficient iterative method for the numerical solution of the Helmholtz equation*. PhD thesis, TU Delft, 2005.

Krylov methods for shifted linear systems

Preconditioning multishift problems

Main disadvantage:

- Preconditioners are in general not easy to apply. For

$$(A - \omega I)M_{\omega}^{-1}y_{\omega} = b, \quad x_{\omega} = M_{\omega}^{-1}y_{\omega}$$

it does **not** hold:

$$\mathcal{K}_m(AM_{\omega}^{-1}, b) \neq \mathcal{K}_m(AM_{\omega}^{-1} - \omega M_{\omega}^{-1}, b)$$

However, there is a way...

References

- Y. A. Erlangga, *A robust and efficient iterative method for the numerical solution of the Helmholtz equation*. PhD thesis, TU Delft, 2005.

The shift-and-invert preconditioner

Can we find M_ω^{-1} such that

$$(A - \omega I)M_\omega^{-1} = AM^{-1} - \eta(\omega)I \quad ?$$

For $M \equiv (A - \sigma I)$, we get:

$$\begin{aligned}(A - \omega I)M_\omega^{-1} &= A(A - \sigma I)^{-1} - \eta(\omega)I \\ &= (1 - \eta(\omega))\underbrace{\left(A + \frac{\sigma\eta(\omega)}{1 - \eta(\omega)}I\right)}_{\equiv -\omega}(A - \sigma I)^{-1}\end{aligned}$$

and, therefore,

$$\begin{aligned}\eta(\omega) &= \frac{\omega}{\omega - \sigma} \\ M_\omega &= \frac{1}{1 - \eta(\omega)}(A - \sigma I) = \frac{1}{1 - \eta(\omega)}M\end{aligned}$$

The shift-and-invert preconditioner

Can we find M_ω^{-1} such that

$$(A - \omega I)M_\omega^{-1} = AM^{-1} - \eta(\omega)I \quad ?$$

For $M \equiv (A - \sigma I)$, we get:

$$\begin{aligned}(A - \omega I)M_\omega^{-1} &= A(A - \sigma I)^{-1} - \eta(\omega)I \\ &= (1 - \eta(\omega))\underbrace{\left(A + \frac{\sigma\eta(\omega)}{1 - \eta(\omega)}I\right)}_{\equiv -\omega}(A - \sigma I)^{-1}\end{aligned}$$

and, therefore,

$$\begin{aligned}\eta(\omega) &= \frac{\omega}{\omega - \sigma} \\ M_\omega &= \frac{1}{1 - \eta(\omega)}(A - \sigma I) = \frac{1}{1 - \eta(\omega)}M\end{aligned}$$

The shift-and-invert preconditioner

Can we find M_ω^{-1} such that

$$(A - \omega I)M_\omega^{-1} = AM^{-1} - \eta(\omega)I \quad ?$$

For $M \equiv (A - \sigma I)$, we get:

$$\begin{aligned}(A - \omega I)M_\omega^{-1} &= A(A - \sigma I)^{-1} - \eta(\omega)I \\ &= (1 - \eta(\omega))\underbrace{\left(A + \frac{\sigma\eta(\omega)}{1 - \eta(\omega)}I\right)}_{\equiv -\omega}(A - \sigma I)^{-1}\end{aligned}$$

and, therefore,

$$\begin{aligned}\eta(\omega) &= \frac{\omega}{\omega - \sigma} \\ M_\omega &= \frac{1}{1 - \eta(\omega)}(A - \sigma I) = \frac{1}{1 - \eta(\omega)}M\end{aligned}$$

FOM preconditioning for flexible Krylov methods

A new idea

What does *flexible* stand for?

- allows a different preconditioner in every iteration
- suggestion: use many shift-and-invert preconditioner
- Can we do better?

References

- A. K. Saibaba, T. Bakhos, P.K. Kitanidis, *A Flexible Krylov Solver for Shifted Systems with Application to Oscillatory Hydraulic Tomography*. Stanford University, 2012.

FOM preconditioning for flexible Krylov methods

A new idea

What does *flexible* stand for?

- allows a different preconditioner in every iteration
- suggestion: use many shift-and-invert preconditioner
- Can we do better?

References

- A. K. Saibaba, T. Bakhos, P.K. Kitanidis, *A Flexible Krylov Solver for Shifted Systems with Application to Oscillatory Hydraulic Tomography*. Stanford University, 2012.

FOM preconditioning for flexible Krylov methods

A new idea

What does *flexible* stand for?

- allows a different preconditioner in every iteration
- suggestion: use many shift-and-invert preconditioner
- Can we do better?

References

- A. K. Saibaba, T. Bakhos, P.K. Kitanidis, *A Flexible Krylov Solver for Shifted Systems with Application to Oscillatory Hydraulic Tomography*. Stanford University, 2012.

FOM preconditioning for flexible Krylov methods

Algorithm 1 Flexible GMRES for $Ax = b$

```
1:  $\mathbf{r}_0 = \mathbf{b} - A\mathbf{x}_0$ ,  $\beta = \|\mathbf{r}_0\|_2$ ,  $\mathbf{v}_1 = \mathbf{r}_0/\beta$ 
2: for  $j = 1$  to  $m$  do
3:   Compute  $\mathbf{z}_j = M_j^{-1}\mathbf{v}_j$ 
4:   Compute  $\mathbf{w} = A\mathbf{z}_j$ 
5:   for  $i = 1$  to  $j$  do
6:      $h_{i,j} = \langle \mathbf{w}, \mathbf{v}_i \rangle$ 
7:      $\mathbf{w} = \mathbf{w} - h_{i,j}\mathbf{v}_i$ 
8:   end for
9:   Set  $h_{j+1,j} = \|\mathbf{w}\|_2$  and  $\mathbf{v}_{j+1} = \mathbf{w}/h_{j+1,j}$ 
10: end for
```

$$\mathbf{x}_m = \mathbf{x}_0 + Z_m \mathbf{y}_m, \text{ where } \mathbf{y}_m = \underset{\mathbf{y}}{\operatorname{argmin}} \|\beta \mathbf{e}_1 - \underline{H}_m \mathbf{y}\|_2$$

References

- Y. Saad, *A flexible inner-outer preconditioned GMRES algorithm*. SIAM J. Sci. Comput., 14, 461-469, 1993.

FOM preconditioning for flexible Krylov methods

Algorithm 1 Flexible GMRES for $Ax = b$

```
1:  $\mathbf{r}_0 = \mathbf{b} - A\mathbf{x}_0$ ,  $\beta = \|\mathbf{r}_0\|_2$ ,  $\mathbf{v}_1 = \mathbf{r}_0/\beta$ 
2: for  $j = 1$  to  $m$  do
3:   Compute  $\mathbf{z}_j = M_j^{-1}\mathbf{v}_j$ 
4:   Compute  $\mathbf{w} = A\mathbf{z}_j$ 
5:   for  $i = 1$  to  $j$  do
6:      $h_{i,j} = \langle \mathbf{w}, \mathbf{v}_i \rangle$ 
7:      $\mathbf{w} = \mathbf{w} - h_{i,j}\mathbf{v}_i$ 
8:   end for
9:   Set  $h_{j+1,j} = \|\mathbf{w}\|_2$  and  $\mathbf{v}_{j+1} = \mathbf{w}/h_{j+1,j}$ 
10: end for
```

$$\mathbf{x}_m = \mathbf{x}_0 + Z_m \mathbf{y}_m, \text{ where}$$
$$\mathbf{y}_m = \underset{\mathbf{y}}{\operatorname{argmin}} \|\beta \mathbf{e}_1 - \underline{H}_m \mathbf{y}\|_2$$

References

- Y. Saad, *A flexible inner-outer preconditioned GMRES algorithm*. SIAM J. Sci. Comput., 14, 461-469, 1993.

FOM preconditioning for flexible Krylov methods

Algorithm 1 Flexible GMRES for $Ax = b$

```
1:  $\mathbf{r}_0 = \mathbf{b} - A\mathbf{x}_0$ ,  $\beta = \|\mathbf{r}_0\|_2$ ,  $\mathbf{v}_1 = \mathbf{r}_0/\beta$ 
2: for  $j = 1$  to  $m$  do
3:   Compute  $\mathbf{z}_j = M_j^{-1}\mathbf{v}_j$ 
4:   Compute  $\mathbf{w} = A\mathbf{z}_j$ 
5:   for  $i = 1$  to  $j$  do
6:      $h_{i,j} = \langle \mathbf{w}, \mathbf{v}_i \rangle$ 
7:      $\mathbf{w} = \mathbf{w} - h_{i,j}\mathbf{v}_i$ 
8:   end for
9:   Set  $h_{j+1,j} = \|\mathbf{w}\|_2$  and  $\mathbf{v}_{j+1} = \mathbf{w}/h_{j+1,j}$ 
10: end for
```

$$\mathbf{x}_m = \mathbf{x}_0 + Z_m \mathbf{y}_m, \text{ where } \mathbf{y}_m = \underset{\mathbf{y}}{\operatorname{argmin}} \|\beta \mathbf{e}_1 - \underline{H}_m \mathbf{y}\|_2$$

References

- Y. Saad, *A flexible inner-outer preconditioned GMRES algorithm*. SIAM J. Sci. Comput., 14, 461-469, 1993.

FOM preconditioning for flexible Krylov methods

A new idea

Our new approach:

Now, we need:

$$(A - \omega I)M_{\omega,j}^{-1} = \alpha_j(\omega)AM_j^{-1} - \beta_j(\omega)I$$

- 1 Solve the preconditioning step with FOM:

$$\mathbf{z}_j = M_j^{-1}\mathbf{v}_j = \text{fom}(A, \mathbf{v}_j)$$

$$\mathbf{z}_j^{(\omega)} = M_{\omega,j}^{-1}\mathbf{v}_j = \text{fom}(A - \omega I, \mathbf{v}_j)$$

- 2 In FOM, residuals of shifted systems are collinear, i.e.:

$$\exists \gamma_j^{(\omega)} \in \mathbb{R} : \quad \gamma_j^{(\omega)} \mathbf{r}_j = \mathbf{r}_j^{(\omega)}$$

FOM preconditioning for flexible Krylov methods

A new idea

- 3 Determine α_j and β_j :

$$\begin{aligned}(A - \omega I)\mathbf{z}_j^{(\omega)} &= \alpha_j A\mathbf{z}_j - \beta_j \mathbf{v}_j \\ \Leftrightarrow \mathbf{v}_j - (A - \omega I)\mathbf{z}_j^{(\omega)} &= \alpha_j \mathbf{v}_j - \alpha_j A\mathbf{z}_j + (1 - \alpha_j + \beta_j)\mathbf{v}_j \\ \Leftrightarrow \mathbf{r}_j &= \underbrace{\alpha_j}_{\equiv \gamma_j^{(\omega)}} \mathbf{r}_j^{(\omega)} + \underbrace{(1 - \alpha_j + \beta_j)}_{\equiv 0} \mathbf{v}_j\end{aligned}$$

- 4 Solve the shifted linear systems with:

$$\gamma_j^{(\omega)} A M_j^{-1} - (\gamma_j^{(\omega)} - 1)I$$

Recap

$$(A - \omega_k I) \mathbf{x}_k = \mathbf{b}, \quad k = 1, \dots, N$$

We want to compare:

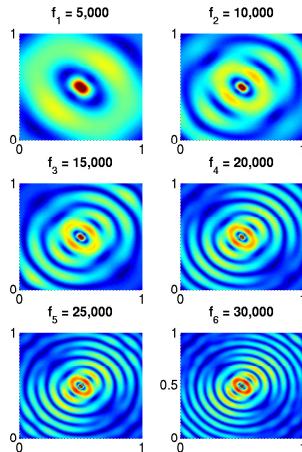
- 1 plain simultaneous solution: msGMRES, msIDR(s)
- 2 using the shift-and-invert preconditioner: pmsGMRES, pmsIDR(s)
- 3 using msFOM within a flexible method: fmsGMRES, fmsIDR(s)

Numerical results

The setting

Test case from literature:

- $\Omega = [0, 1] \times [0, 1]$
- $h = 0.01$ implying
 $n = 10.201$ grid points
- system size:
 $4n = 40.804$
- $N = 6$ frequencies
- point source at center

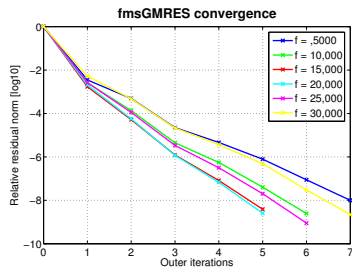
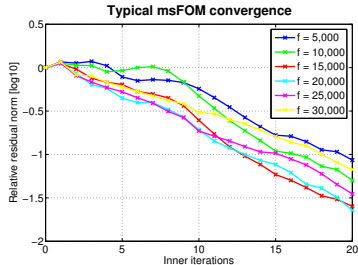
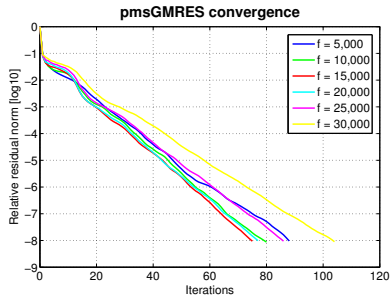


References

- T. Airaksinen, A. Pennanen, J. Toivanen, *A damping preconditioner for time-harmonic wave equations in fluid and elastic material*. Journal of Computational Physics, 2009.

Numerical results

Convergence behavior



Numerical results

Time measurements

For a fair time comparison:

- optimize the (complex) *seed shift* σ ,
- optimize number of inner msFOM iterations,
- guarantee same order of relative residuals at convergence.

	msK	pmsK	fmsK
K = GMRES	$>63k$	16.21	7.69
K = IDR(1)	-	18.42	8.65
K = IDR(4)	-	17.16	8.83
K = IDR(8)	617.5	24.10	7.88

Discussion and Outlook

My plan for the next months...

① Consider the marmousi2 model (right):

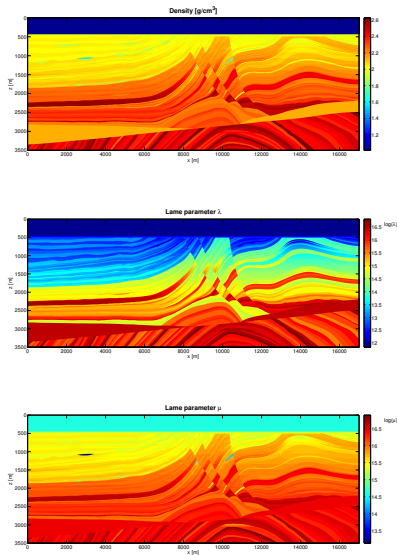
- ▶ parameters

$\rho_s(\mathbf{x})$, $\mu(\mathbf{x})$, $\lambda(\mathbf{x})$
depend on space

- ▶ $\sim 40,000,000$ grid points

② Improve flexible pre-conditioning

- ▶ avoid LU decomposition
- ▶ publication



Discussion and Outlook

Large-scale outlook...

- High performance computing
 - ▶ When is a good point to switch from MATLAB to e.g. C++ or Python?
 - ▶ Make use of parallel architecture, i.e. use MPI and/or Cuda.
- Consider many right-hand sides:

$$(A - \omega_k I) \mathbf{x}_k = \mathbf{b}_\ell, \quad k = 1, \dots, N, \quad \ell = 1, \dots, M$$

- Solve inverse problem:

$$\min_{\rho_s, \lambda, \mu} \|\mathbf{u}_{sim}^{(\omega_k)} - \mathbf{u}_{data}^{(\omega_k)}\|_2 \quad s.t. \quad \mathbf{f}(\mathbf{u}_{sim}, \omega_k, \rho_s, \lambda, \mu) = 0$$

Discussion and Outlook

Large-scale outlook...

- High performance computing
 - ▶ When is a good point to switch from MATLAB to e.g. C++ or Python?
 - ▶ Make use of parallel architecture, i.e. use MPI and/or Cuda.
- Consider many right-hand sides:

$$(A - \omega_k I) \mathbf{x}_k = \mathbf{b}_\ell, \quad k = 1, \dots, N, \quad \ell = 1, \dots, M$$

- Solve inverse problem:

$$\min_{\rho_s, \lambda, \mu} \|\mathbf{u}_{sim}^{(\omega_k)} - \mathbf{u}_{data}^{(\omega_k)}\|_2 \quad s.t. \quad \mathbf{f}(\mathbf{u}_{sim}, \omega_k, \rho_s, \lambda, \mu) = 0$$

Discussion and Outlook

Large-scale outlook...

- High performance computing
 - ▶ When is a good point to switch from MATLAB to e.g. C++ or Python?
 - ▶ Make use of parallel architecture, i.e. use MPI and/or Cuda.
- Consider many right-hand sides:

$$(A - \omega_k I) \mathbf{x}_k = \mathbf{b}_\ell, \quad k = 1, \dots, N, \quad \ell = 1, \dots, M$$

- Solve inverse problem:

$$\min_{\rho_s, \lambda, \mu} \|\mathbf{u}_{sim}^{(\omega_k)} - \mathbf{u}_{data}^{(\omega_k)}\|_2 \quad s.t. \quad \mathbf{f}(\mathbf{u}_{sim}, \omega_k, \rho_s, \lambda, \mu) = 0$$