

The Nonlinear Eigenvalue Problem: Part II

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Two lectures:

- ▶ Part I: Mathematical properties of nonlinear eigenproblems (NEPs)
 - Definition and historical aspects
 - Examples and applications
 - Solution structure

- ▶ Part II: Numerical methods for NEPs
 - Solvers based on Newton's method
 - Solvers using contour integrals
 - Linear interpolation methods

S. GÜTTEL AND F. TISSEUR, *The nonlinear eigenvalue problem*.
Acta Numerica 26:1–94, 2017.

Solvers Based on Newton's Method

- Newton's method is a natural approach to compute e'vals/e'vecs of NEPs provided good initial guesses are available. Local quadratic convergence.
- Initial guess is the only crucial parameter \Rightarrow great advantage over other NEP eigensolvers.
- Two broad ways NEP $F(\lambda)v = 0$ can be tackled by a Newton-type method:
 - ▶ Apply Newton's method to a scalar equation $f(z) = 0$ whose roots are the wanted e'vals of F .
 - ▶ Apply Newton's method directly to the vector problem $F(\lambda)v = 0$ together with some normalization condition on v .

Newton's Method for Scalar Function

Most obvious approach: Find roots of $f(z) = \det F(z)$.

Combining Newton's method with Jacobi's formula

$$\lambda^{(k+1)} = \lambda^{(k)} - \frac{f(\lambda^{(k)})}{f'(\lambda^{(k)})}$$

$$f'(z) = \det F(z) \operatorname{trace}(F(z)^{-1} F'(z)),$$

we obtain the **Newton-trace iteration** [Lancaster 1966]

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Potential problems:

- Inverse of nearly singular $F(\lambda^{(k)})$ as $\lambda^{(k)} \rightarrow \lambda$.
- Requires $F'(z)$ explicitly. Computationally expensive.
- Initialization?

Newton's Method for Scalar Function (Cont.)

Kublanovskaya $f(z) = r_{nn}(z)$, where $r_{nn}(z)$ is (n, n) entry of R in **rank-revealing QR** decomposition of $F(z)$,

$$F(z)\Pi(z) = Q(z)R(z).$$

This yields the **Newton-QR iteration** for a root of $r_{nn}(z)$,

$$\lambda^{(k+1)} = \lambda^{(k)} - 1 / (\mathbf{e}_n^T \mathbf{Q}_k^* F'(\lambda^{(k)}) \Pi_k R_k^{-1} \mathbf{e}_n).$$

At convergence, we can take $x = \Pi_k R_k^{-1} \mathbf{e}_n$, $y = \mathbf{Q}_k \mathbf{e}_n$ as approx for the right and left e'vecs of the converged e'val.

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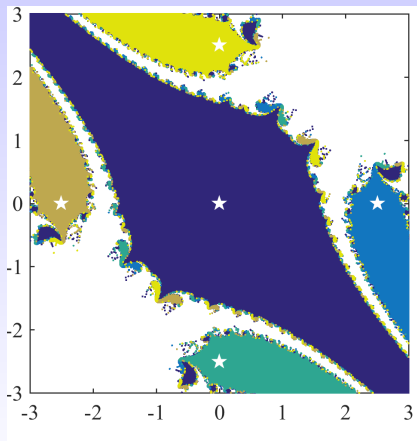
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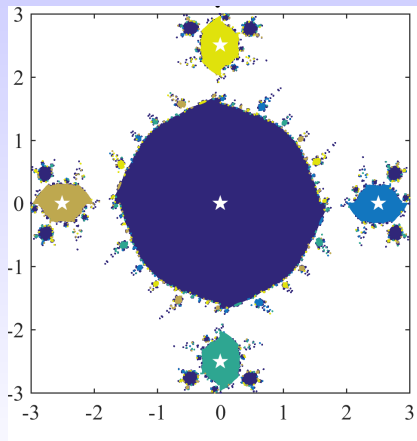
- ▶ Garret, Bai and Li (2016) propose an efficient implementation for large banded NEPs.
- ▶ MATLAB and C++ implementations including deflation are publicly available.

Convergence basins

$F(z) = \begin{bmatrix} e^{iz^2} & 1 \\ 1 & 1 \end{bmatrix}$ has e'vals $0, \pm\sqrt{2\pi}, \pm i\sqrt{2\pi}$ in
 $\Omega = \{z \in \mathbb{C} : -3 \leq \operatorname{Re}(z) \leq 3, -3 \leq \operatorname{Im}(z) \leq 3\}$.



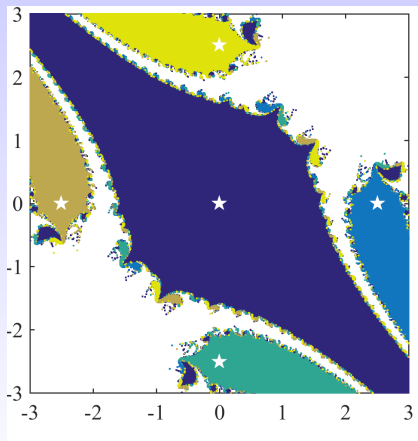
Newton-trace method



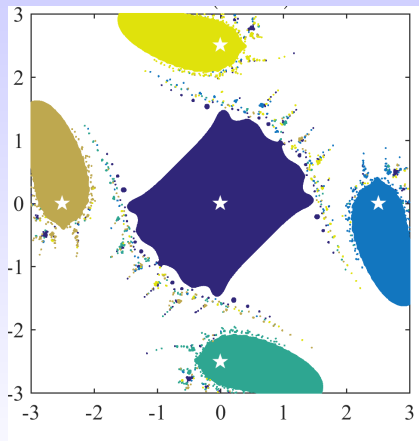
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Newton-trace method



Newton-trace (secant) method

Newton-QR for Banded NEP

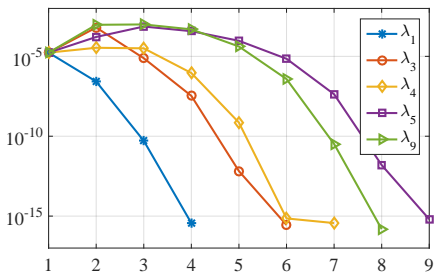
Consider the `loaded_string` problem defined by

$$F(\lambda)v = \left(C_1 - \lambda C_2 + \frac{\lambda}{\lambda - \sigma} C_3 \right) v = 0$$

with C_1, C_2 tridiagonal and $C_3 = e_n e_n^T$. $n = 100$.

Use `NQR4UB` [Garret and Li (2013)] to compute the 5 e'vals in `[4, 296]` with `lambda0 = 4`.

Residuals $|r_{nn}(\lambda)| / \|F(\lambda)\|_F$ at each iter.



$$\eta_F(\lambda_i, v_i) = \frac{\|F(\lambda_i)v_i\|_2}{\|F(\lambda_i)\|_F \|v_i\|_2}$$

i	λ_i	$\eta_F(\lambda_i, v_i)$	$\eta_F(\lambda_i, w_i^*)$
1	4.482	3.5e-17	3.7e-16
3	63.72	3.1e-17	2.1e-16
4	123.0	2.7e-17	9.2e-17
5	202.2	4.9e-17	5.4e-16
9	719.4	3.5e-17	1.8e-16

Other Variants

Many variations based on **scalar root finding** exist:

- Newton-LU [Yang 1983, Wobst 1987]
- BDS (bordered, deletion, substitution) method [Andrew/Chu/Lancaster 1995]
- implicit determinant method [Spence/Poulton 2005]

Newton's Method for Vector Equation

Applying Newton's method to $\mathcal{N} \begin{bmatrix} v \\ \lambda \end{bmatrix} = 0$ where

$$\mathcal{N} \begin{bmatrix} v \\ \lambda \end{bmatrix} = \begin{bmatrix} F(\lambda)v \\ u^*v - 1 \end{bmatrix}$$

leads to the Newton's iteration

$$\begin{bmatrix} v^{(k+1)} \\ \lambda^{(k+1)} \end{bmatrix} = \begin{bmatrix} v^{(k)} \\ \lambda^{(k)} \end{bmatrix} - \begin{bmatrix} F(\lambda^{(k)}) & F'(\lambda^{(k)})v^{(k)} \\ u^* & 0 \end{bmatrix}^{-1} \begin{bmatrix} F(\lambda^{(k)})v^{(k)} \\ u^*v^{(k)} - 1 \end{bmatrix}.$$

Other variants include

- nonlinear inverse iteration [Unger 1950, Ruhe 1973]
- two-sided Rayleigh functional iteration [Schreiber 2008]
- residual inverse iteration [Neumaier 1985]

Iterative Projection Methods for NEPs

Let $U \in \mathbb{C}^{n \times k}$ with $k \ll n$ and $U^*U = I_k$ (**search space**) and $Q \in \mathbb{C}^{n \times k}$, $Q^*Q = I_k$ (test space). Instead of solving $F(\lambda)v = 0$, solve $k \times k$ projected NEP $Q^*F(\vartheta)Ux = 0$ (*)

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Let (ϑ, x) be an e'pair of (\star) .

- If $\|F(\vartheta)Ux\|$ is small enough, accept (ϑ, Ux) as an approximate e'pair for F .
- If not, extend search space into $\text{span}\{U, \Delta v\}$ by one step of Newton iteration with initial guess (ϑ, Ux) . Δv solves the **Jacobi–Davidson correction eqn**:

$$(I_n - F'(\vartheta)vq^*)F(\vartheta)(I_n - vv^*)\Delta v = -F(\vartheta)v.$$

(Does not need to be solved accurately.)

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Variations of Jacobi–Davidson for NEPs are proposed by [Hochstenbach and Sleijpen (2003)], [Betcke and Voss (2004)], [Voss (2007)] and [Effenberger (2013)].

Deflation of Computed Eigenpairs

- Prevent the iteration from converging to already computed eigenpairs.
- Maps the already computed eigenvalues to infinity.

Suppose we have computed ℓ simple e'vals of F , $\lambda_1, \dots, \lambda_\ell$ and let $x_i, y_i \in \mathbb{C}^n$ be s.t. $y_i^* x_i = 1$, $i = 1, \dots, \ell$. Let

$$\tilde{F}(z) = F(z) \prod_{i=1}^{\ell} \left(I - \frac{z - \lambda_i - 1}{z - \lambda_i} y_i x_i^* \right).$$

Then $\Lambda(\tilde{F}) = \Lambda(F) \cup \{\infty\} \setminus \{\lambda_1, \dots, \lambda_\ell\}$.

If \tilde{v} is an e'vec of \tilde{F} with e'val λ then

$$v = \prod_{i=1}^{\ell} \left(I - \frac{z - \lambda_i - 1}{z - \lambda_i} y_i x_i^* \right) \tilde{v}$$

is an e'vec of F associated with the e'val λ .

[Ferng et al. (2001)], [Huang et al. (2016)].

Robust Successive Computation of Eigenpairs

- Suppose we have already computed a **minimal invariant pair** $(V, M) \in \mathbb{C}^{n \times m} \times \mathbb{C}^{m \times m}$ for F .
- Extend (V, M) into one size larger minimal invariant pair

$$(\widehat{V}, \widehat{M}) = \left([V \quad x], \begin{bmatrix} M & b \\ 0 & \lambda \end{bmatrix} \right) \in \mathbb{C}^{n \times (m+1)} \times \mathbb{C}^{(m+1) \times (m+1)}.$$

[Effenberger (2013)] shows that $(\lambda, \begin{bmatrix} x \\ b \end{bmatrix})$ is an eigenpair of an $(n+m) \times (n+m)$ NEP $\widetilde{F}(\lambda) \begin{bmatrix} x \\ b \end{bmatrix} = 0$.

- Solve $\widetilde{F}(\lambda) \begin{bmatrix} x \\ b \end{bmatrix} = 0$ by any of the previous methods.

Block-Newton Method

$(V, M) \in \mathbb{C}^{n \times m} \times \mathbb{C}^{m \times m}$ is an invariant pair for $F \in H(\Omega, \mathbb{C}^{n \times n})$ if

$$\mathcal{F}(V, M) = C_1 V f_1(\Lambda) + C_2 V f_2(\Lambda) + \cdots + C_\ell V f_\ell(\Lambda) = \mathbf{0}_{n \times m}.$$

Add normalization condition:

$$\mathcal{N}(V, M) = \mathbf{0}_{m \times m}.$$

[Kressner (2009)] showed that (V, M) is complete iff Jacobian

$$\begin{aligned} \mathcal{M} : \mathbb{C}^{n \times m} \times \mathbb{C}^{m \times m} &\rightarrow \mathbb{C}^{n \times m} \times \mathbb{C}^{m \times m} \\ (\Delta V, \Delta M) &\mapsto (L_{\mathcal{F}}(\Delta V, \Delta M), L_{\mathcal{N}}(\Delta V, \Delta M)) \end{aligned}$$

is invertible. Newton correction $(\Delta V, \Delta M)$ satisfies

$$\mathcal{M}(\Delta V, \Delta M) = -(\mathcal{F}(V, M), \mathbf{0}_{m \times m}).$$

Safeguarded Iteration for Hermitian NEPs

Assume $F(\bar{z}) = F(z)^*$ for all $z \in \mathbb{C}$ and that if λ_k is a k th eigenvalue of $F(z)$ (i.e., $\mu = 0$ is the k th largest eigenvalue of the Hermitian matrix $F(\lambda_k)$), then (see Part I)

$$\lambda_k = \min_{\substack{V \in \mathcal{S}_k \\ V \cap \mathbb{K}(\rho) \neq \emptyset}} \max_{\substack{x \in V \cap \mathbb{K}(\rho) \\ x \neq 0}} \rho(x) \in \mathbb{I}.$$

This suggests the **safeguarded iteration** [Werner 1970]:

- 1 Choose an initial approx $\lambda^{(0)}$ to j th e'val of F .
- 2 For $k = 0, 1, \dots$ until convergence
- 3 Compute e'vec $x^{(k)}$ of j th largest e'val of $F(\lambda^{(k)})$.
- 4 Compute real root ρ of $x^{(k)*} F(\rho) x^{(k)} = 0$ closest to $\lambda^{(k)}$
- 5 set $\lambda^{(k+1)} = \rho$.
- 6 end

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Local quadratic convergence [Niendorf and Voss (2010)].

Methods Based on Contour Integration

Given $F \in H(\Omega, \mathbb{C}^{n \times n})$. By Keldysh's theorem we have

$$F(z)^{-1} = V(zI - J)^{-1}W^* + R(z)$$

on some closed set $\Sigma \subset \Omega$, where J is an $m \times m$ Jordan block matrix containing all the eigenvalues $\Lambda(F) \cap \Sigma$.

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Let $\Gamma \subset \Omega$ be a contour enclosing the eigenvalues of J , let $X \in \mathbb{C}^{n \times r}$ be a “probing matrix”, and $f \in H(\Omega, \mathbb{C})$ (**filter function**). Then

$$\begin{aligned}A_f &:= \frac{1}{2\pi i} \int_{\Gamma} f(z)F(z)^{-1}X\delta z \\ &= \frac{1}{2\pi i} \int_{\Gamma} f(z)V(zI - J)^{-1}W^*X\delta z \\ &= Vf(J)W^*X.\end{aligned}$$

Beyn's Integral Approach

Construct

$$A_0 := \frac{1}{2\pi i} \int_{\Gamma} F(z)^{-1} X \delta z = V W^* X$$
$$A_1 := \frac{1}{2\pi i} \int_{\Gamma} z F(z)^{-1} X \delta z = V J W^* X.$$

Assuming that V , W , and $W^* X$ are of full rank m ,
can show that e'vals of $\lambda A_0 - A_1$ are e'vals of F inside Γ .

[Asakura 2009] [Beyn 2012] [Yokota/Sakurai 2013]

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Other filter functions f can be used via

$A_f = \frac{1}{2\pi i} \int_{\Gamma} f(z) F(z)^{-1} X \delta z$ leading to **higher-order moments**.

[Murakami '10] [Güttel et al '15] [Austin/Trefethen '15] [Van Barel '16]

Quadrature

The contour integrals involved in A_0 and A_1 are approximated by numerical quadrature.

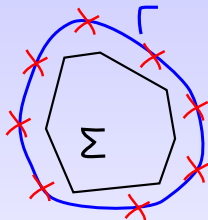
Let $\gamma : [0, 1] \rightarrow \Gamma$ be a parameterization, then

$$A_{j,n_c} = \sum_{\ell=1}^{n_c} \omega_\ell z^\ell F(\gamma(t_\ell))^{-1} X \approx A_j$$

is a quadrature approximation with n_c nodes ($j = 1, 2$).

Note that the n_c solves $F(\gamma(t_\ell))^{-1} X$ are completely decoupled and can be assigned to different processors.

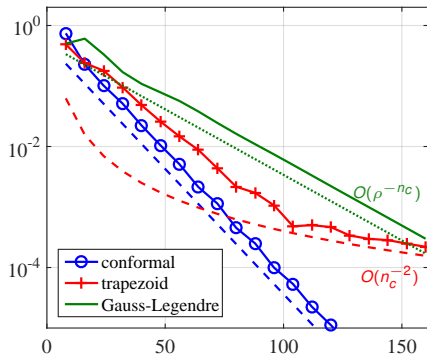
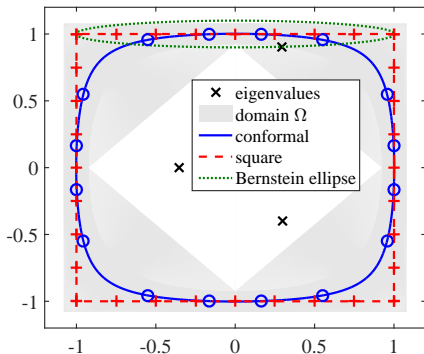
⇒ Great potential for parallelization!



Care has to be taken with the quadrature rule

The quality of the quadrature approximation determines the accuracy of the computed e'vals [Beyn 2012] [Güttel/T. 2017].

Example: Quadrature errors $\|A_j - A_{j,n_c}\|$ as n_c increases (right) with different quadrature rules on (almost) square contour (left).



Methods based on linear interpolation

Instead of solving $F(\lambda)v = 0$ directly, we may approximate $F \approx R_m$ on $\Sigma \subseteq \mathbb{C}$ by simpler NEP and solve $R_m(\lambda)v = 0$.

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Practical approach: Rational form

$$R_m(z) = b_0(z)D_0 + b_1(z)D_1 + \cdots + b_m(z)D_m$$

where $D_j \in \mathbb{C}^{n \times n}$ are fixed and b_j are rational functions.

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Particularly useful: (scaled) rational Newton basis

$$b_0(z) \equiv 1, \quad b_{j+1}(z) = \frac{z - \sigma_j}{\beta_{j+1}(1 - z/\xi_{j+1})} b_j(z)$$

with interpolation points $\sigma_j \in \Sigma$ and poles $\xi_j \in \overline{\mathbb{C}} \setminus \Sigma$.

Choice of σ_j, ξ_j, β_j by NLEIGS sampling [Güttel et al 2014].

NLEIGS sampling

Assume F is holomorphic on $\Omega = \mathbb{C} \setminus \Xi$ and we target the eigenvalues in $\Sigma \subseteq \Omega$.

Assume we have chosen nodes $\sigma_0, \sigma_1, \dots, \sigma_m \in \Sigma$ and poles $\xi_1, \dots, \xi_m \in \Xi$. Define $\mathbf{s}_m(z) := (z - \sigma_m)\mathbf{b}_m(z)$.

By the **Hermite–Walsh formula** we have

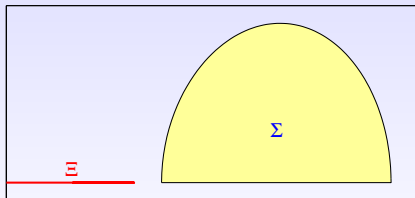
$$F(z) - R_m(z) = \frac{1}{2\pi i} \int_{\Gamma} \frac{\mathbf{s}_m(z)}{\mathbf{s}_m(\zeta)} \frac{F(\zeta)}{\zeta - z} d\zeta,$$

and so the **uniform approximation error on Σ** satisfies

$$\|F - R_m\|_{\Sigma} := \max_{z \in \Sigma} \|F(z) - R_m(z)\|_2 \leq C \|\mathbf{s}_m\|_{\Sigma} \cdot \|\mathbf{s}_m^{-1}\|_{\Gamma}$$

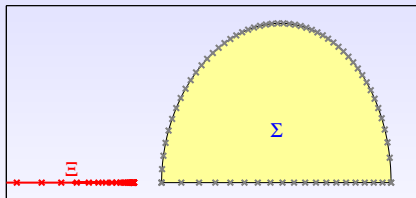
Aim: Make \mathbf{s}_m small on Σ and large on Γ .

NLEIGS sampling of F on Σ



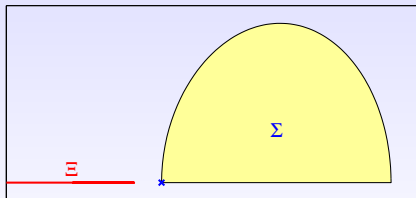
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1. Discretize boundaries of Σ and Ξ sufficiently fine.



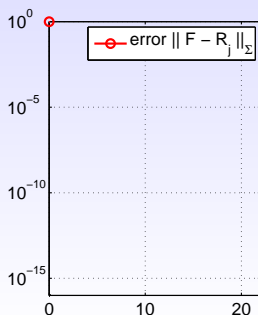
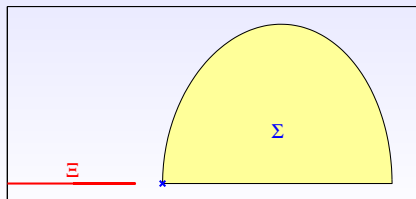
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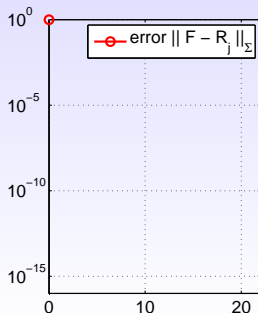
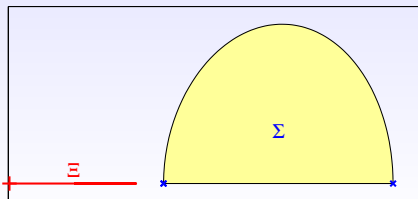
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3. For $j = 1, 2, \dots, m$ choose σ_j and ξ_j such that

$$\max_{z \in \Sigma} |s_{j-1}(z)| = |s_{j-1}(\sigma_j)| \quad \text{and} \quad \min_{z \in \Xi} |s_{j-1}(z)| = |s_{j-1}(\xi_j)|.$$

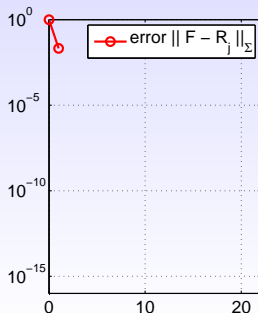
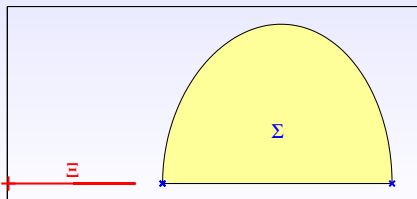


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Choose β_j such that $\|s_j\|_{\Sigma} = 1$ and set $D_j = \frac{F(\sigma_j) - R_{j-1}(\sigma_j)}{b_j(\sigma_j)}$.

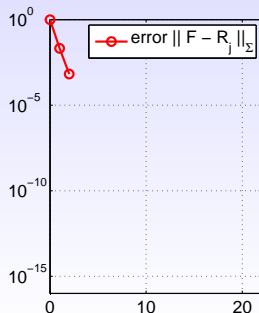
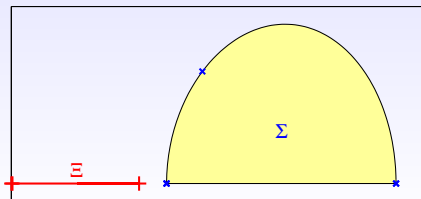


NLEIGS sampling of F on Σ

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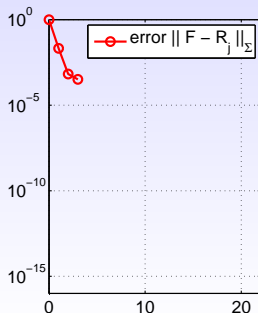
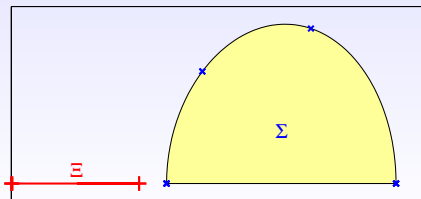


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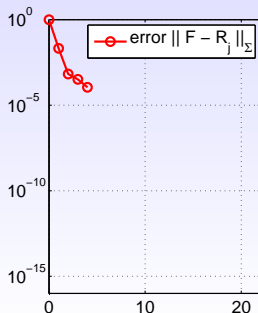
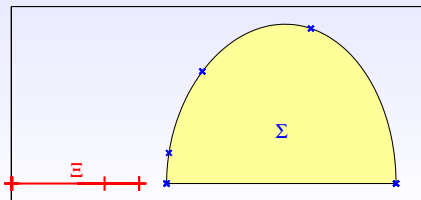


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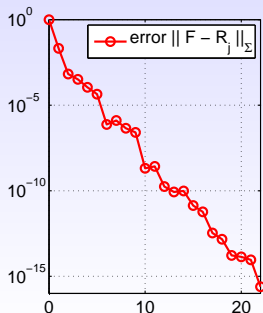
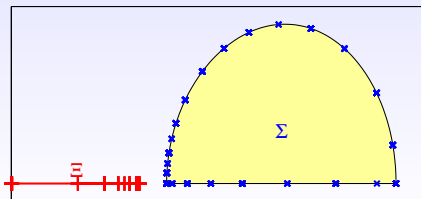


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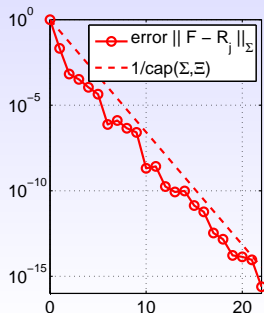
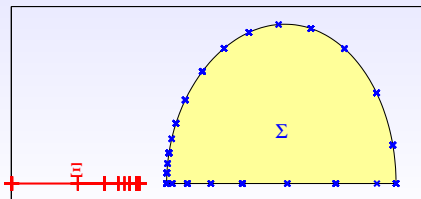


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Interpolation techniques can be combined with

- linearization of $R_m \Rightarrow$ structured GEP $A_m x = \lambda B_m x$
- rational Krylov algorithms for solving GEP
- dynamic increase of degree m during Krylov iteration
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NLEIGS implementations are available in the

- SLEPc library version 3.7 [Campos & Roman 2016]
- Rational Krylov Toolbox [Berljafa & Güttel 2015].

Concluding Remarks

NEPs have interesting mathematical properties. They arise in many applications and their efficient solution requires ideas from numerical linear algebra, complex analysis, and approximation theory (among other fields).

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There is more to be said, e.g.,

- Structured NEPs?
- Higher-order integral moments
- Preconditioning/scaling of linearizations
- Implementation, software packages

References I



A. L. Andrew, K. E. Chu, and P. Lancaster.

On the numerical solution of nonlinear eigenvalue problems.

Computing, 55:91–111, 1995.



J. Asakura, T. Sakurai, H. Tadano, T. Ikegami, and K. Kimura.

A numerical method for nonlinear eigenvalue problems using contour integral.

JSIAM Letters, 1:52–55, 2009.

References II



M. Berljafa and S. Güttel.

A Rational Krylov Toolbox for MATLAB.

MIMS EPrint 2014.56, Manchester Institute for Mathematical Sciences, The University of Manchester, UK, 2014.

Available for download at <http://rktoolbox.org/>.



T. Betcke and H. Voss.

A Jacobi–Davidson-type projection method for nonlinear eigenvalue problems.

Future Generation Computer Systems, 20(3):363–372, 2004.



W.-J. Beyn.

An integral method for solving nonlinear eigenvalue problems.

Linear Algebra Appl., 436(10):3839–3863, 2012.



C. Campos and J. E. Roman.

Parallel Krylov solvers for the polynomial eigenvalue problem in SLEPc.

SIAM J. Sci. Comput., 38(5):S385–S411, 2016.





C. Effenberger.

Robust successive computation of eigenpairs for nonlinear eigenvalue problems.

SIAM J. Matrix Anal. Appl., 34(3):1231–1256, 2013.

References IV

-  W. R. Ferng, W.-W. Lin, D. J. Pierce, and C.-S. Wang.
Nonequivalence transformation of λ -matrices eigenproblems
and model embedding approach to model tuning.
Numer. Linear Algebra Appl., 8(1):53–70, 2001.
-  C. K. Garrett, Z. Bai, and R.-C. Li.
A nonlinear QR algorithm for banded nonlinear eigenvalue
problems.
ACM Trans. Math. Software, 43(1):4:1–4:19, 2016.



C. K. Garrett and R.-C. Li.

Unstructurally banded nonlinear. eigenvalue solver software, 2013.

<http://www.csm.ornl.gov/newsite/software.html>.






S. Güttel and F. Tisseur.

The nonlinear eigenvalue problem.

In *Acta Numerica*, volume 26, pages 1–94. Cambridge University Press, 2017.

References VI

-  S. Güttel, R. Van Beeumen, K. Meerbergen, and W. Michiels.
NLEIGS: A class of fully rational Krylov methods for nonlinear eigenvalue problems.
SIAM J. Sci. Comput., 36(6):A2842–A2864, 2014.
-  M. E. Hochstenbach and G. L. Sleijpen.
Two-sided and alternating Jacobi–Davidson.
Linear Algebra Appl., 358(1):145–172, 2003.
-  T.-M. Huang, W.-W. Lin, and V. Mehrmann.
A Newton-type method with nonequivalence deflation for nonlinear eigenvalue problems arising in photonic crystal modeling.
SIAM J. Sci. Comput., 38(2):B191–B218, 2016.



E. Jarlebring, K. Meerbergen, and W. Michiels.

The infinite Arnoldi method and an application to time-delay systems with distributed delay.

In R. Sipahi, T. Vyhlídal, S.-I. Niculescu, and P. Pepe, editors, *Time Delay Systems: Methods, Applications and New Trends*, volume 423 of *Lecture Notes in Control and Information Sciences*, pages 229–239. Springer-Verlag, Berlin, 2012.



D. Kressner.

A block Newton method for nonlinear eigenvalue problems.

Numer. Math., 114(2):355–372, 2009.

References VIII



V. N. Kublanovskaya.

On an approach to the solution of the generalized latent value problem for λ -matrices.

SIAM J. Numer. Anal., 7:532–537, 1970.



P. Lancaster.

Lambda-Matrices and Vibrating Systems.

Pergamon Press, Oxford, 1966.

ISBN 0-486-42546-0.

Reprinted by Dover, New York, 2002.

References IX



D. Lu, Y. Su, and Z. Bai.

Stability analysis of the two-level orthogonal Arnoldi procedure.

SIAM J. Matrix Anal. Appl., 37(1):195–214, 2016.



A. Neumaier.

Residual inverse iteration for the nonlinear eigenvalue problem.

SIAM J. Numer. Anal., 22(5):914–923, 1985.



V. Niendorf and H. Voss.

Detecting hyperbolic and definite matrix polynomials.

Linear Algebra Appl., 432:1017–1035, 2010.

References X



A. Ruhe.

Algorithms for the nonlinear eigenvalue problem.

SIAM J. Numer. Anal., 10:674–689, 1973.



K. Schreiber.

Nonlinear Eigenvalue Problems: Newton-type methods and Nonlinear Rayleigh Functionals.

PhD thesis, Technischen Universität Berlin, Germany, 2008.



A. Spence and C. Poulton.

Photonic band structure calculations using nonlinear eigenvalue techniques.

J. Comput. Phys., 204(1):65–81, 2005.



H. Unger.

Nichtlineare Behandlung von Eigenwertaufgaben.

ZAMM Z. Angew. Math. Mech., 30(8-9):281–282, 1950.



M. Van Barel.

Designing rational filter functions for solving eigenvalue problems by contour integration.

Linear Algebra Appl., 502:346–365, 2016.



R. Van Beeumen, K. Meerbergen, and W. Michiels.

Compact rational Krylov methods for nonlinear eigenvalue problems.

SIAM J. Matrix Anal. Appl., 36(2):820–838, 2015.



H. Voss.

A Jacobi–Davidson method for nonlinear and nonsymmetric eigenproblems.

Computers and Structures, 85:1284–1292, 2007.



B. Werner.

Das Spektrum von Operatorenscharen mit verallgemeinerten Rayleighquotienten.

PhD thesis, Universität Hamburg, Hamburg, Germany, 1970.



R. Wobst.

The generalized eigenvalue problem and acoustic surface wave computations.

Computing, 39:57–69, 1987.

References XIII



W. H. Yang.

A method for eigenvalues of sparse λ -matrices.

Internat. J. Numer. Methods Eng., 19:943–948, 1983.



S. Yokota and T. Sakurai.

A projection method for nonlinear eigenvalue problems using contour integrals.

JSIAM Letters, 5:41–44, 2013.