

Oberwolfach Workshop “Numerical Solution of PDE Eigenvalue Problems”

Mathematisches Forschungsinstitut Oberwolfach
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Computation of the \mathcal{H}_∞ -Norm for Large-Scale Systems

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- 1 Introduction
- 2 Method 1: Optimization over Structured Pseudospectra
- 3 Method 2: Optimization Using Even Matrix Pencils
- 4 Comparison
- 5 Summary and Open Questions

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Continuous-Time Descriptor Systems

Given: Continuous-time LTI descriptor system

$$\Sigma : \begin{cases} E\dot{x}(t) = Ax(t) + Bu(t), \\ y(t) = Cx(t) \end{cases}$$

- $E, A \in \mathbb{R}^{n \times n}$, $B \in \mathbb{R}^{n \times m}$, $C \in \mathbb{R}^{p \times n}$, $m, p \ll n$,
- descriptor vector $x(t) \in \mathbb{R}^n$, input vector $u(t) \in \mathbb{R}^m$, output vector $y(t) \in \mathbb{R}^p$.
- **Assumptions:** $\lambda E - A$ is **regular**, all matrices are **large and sparse**.

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Frequency domain representation

$$\text{Transfer function } G(s) := C(sE - A)^{-1}B$$

\mathcal{H}_∞ -Spaces and \mathcal{H}_∞ -Norm

Definition: the space $\mathcal{H}_\infty^{p \times m}$

$\mathcal{H}_\infty^{p \times m}$ – Hardy space of $p \times m$ functions of the form

$$G(s) = C(sE - A)^{-1}B$$

which are analytic and bounded in the open right half-plane, i.e., they are

- **well-defined** ($\lambda E - A$ regular);
- **stable** (all poles in open left half-plane);
- **proper** (bounded at infinity).

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Definition: \mathcal{H}_∞ -norm

Natural norm for the space $\mathcal{H}_\infty^{p \times m}$:

$$\|G\|_{\mathcal{H}_\infty} := \sup_{s \in \mathbb{C}^+} \sigma_{\max}(G(s)) = \sup_{\omega \in \mathbb{R}} \sigma_{\max}(G(i\omega)).$$

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\mathcal{H}_∞ -Norm and Structured Complex Stability Radius

What happens to stability/properness if we perturb G ?

Consider the perturbed transfer function

$$G_\Delta(s) := C(sE - (A + B\Delta C))^{-1}B$$

with $\Delta \in \mathbb{C}^{m \times p}$.

Question

What is the smallest ε such that $G_\Delta \notin \mathcal{H}_\infty^{p \times m}$ for some $\|\Delta\|_2 < \varepsilon$?
 \rightsquigarrow structured complex stability radius $r_{\mathbb{C}}(E, A, B, C)$

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Connection to the \mathcal{H}_∞ -norm

$$r_{\mathbb{C}}(E, A, B, C) = \begin{cases} \|G\|_{\mathcal{H}_\infty}^{-1} & \text{if } G \not\equiv 0, \\ \infty & \text{if } G \equiv 0. \end{cases}$$

[HINRICHSSEN, PRITCHARD '86, BENNER, V. '13]

How to Compute $r_{\mathbb{C}}(E, A, B, C)$?

Distinction of Cases

Let Δ be the “smallest” perturbation with $G_{\Delta} \notin \mathcal{H}_{\infty}^{p \times m}$. Two cases:

- $G_{\Delta}(\cdot)$ is **improper** or **not well-defined** \rightsquigarrow needs special treatment;
- $G_{\Delta}(\cdot)$ is **unstable** \rightsquigarrow analysis of finite poles.

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Definitions

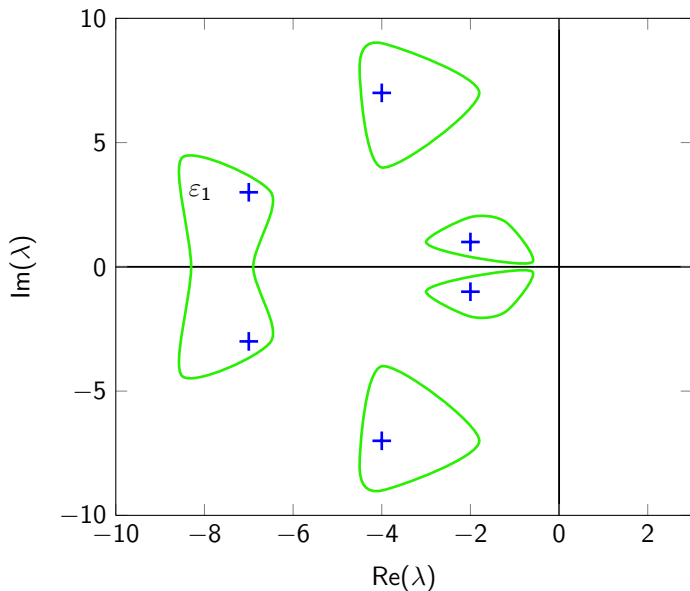
- set of finite poles of $G(\cdot)$ denoted by $\Pi_f(E, A, B, C)$,
- structured pseudospectrum $\Pi_{\varepsilon}(E, A, B, C)$:

$$\Pi_{\varepsilon}(E, A, B, C) = \{s \in \mathbb{C} : s \in \Pi_f(E, A + B\Delta C, B, C) \text{ for } \Delta \in \mathbb{C}^{m \times p} \text{ with } \|\Delta\|_2 < \varepsilon\},$$

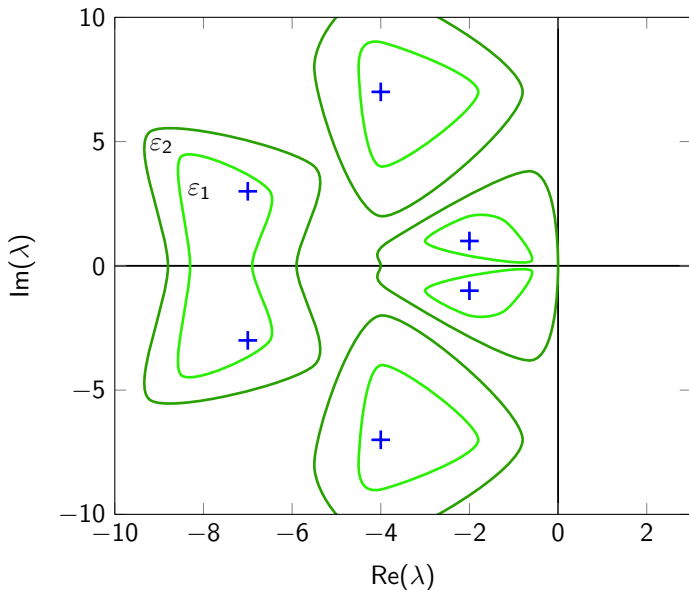
- structured pseudospectral abscissa $\alpha(\varepsilon)$:

$$\alpha(\varepsilon) := \max \{\operatorname{Re} s : s \in \Pi_{\varepsilon}(E, A, B, C)\}.$$

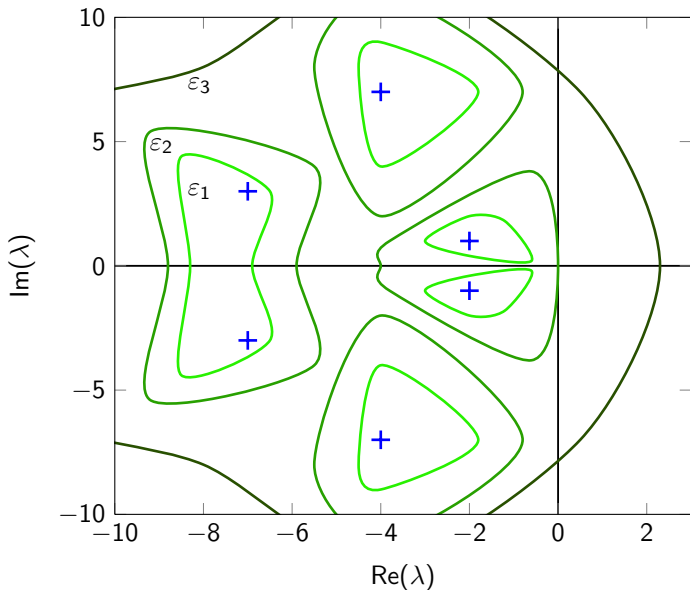
Graphical Interpretation



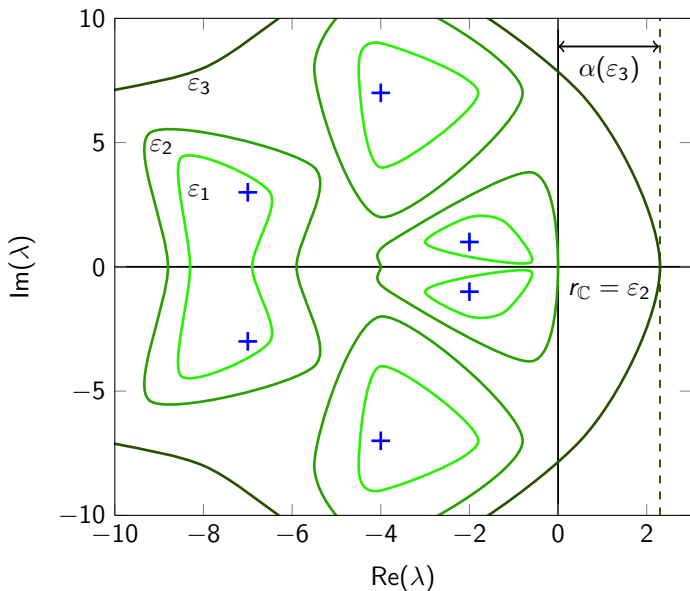
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Algorithm Outline

Finding $r_{\mathbb{C}}(E, A, B, C)$ is equivalent to finding the (unique) root of $\alpha(\cdot)$.
Derivative of $\alpha(\cdot)$ can be computed! \rightsquigarrow **Newton's method applicable.**

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Sketch of the algorithm

- 1 Choose initial ε .
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Computation of $\alpha(\varepsilon)$ – Perturbation Strategy

“Theorem”

The whole structured pseudospectrum can be obtained by using only rank-1 perturbations, i.e., $\Delta = uv^H$ with vectors u, v .

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Strategy

[GUGLIELMI, OVERTON '11]

Compute a sequence of suitable structured rank-1 perturbed pencils $\lambda E - (A + \varepsilon Buv^H C)$ such that one of the perturbed eigenvalues converges to the rightmost pseudoeigenvalue of $\lambda E - A$!

First-Order Perturbation Theory

Lemma

[STEWART, SUN '90]

Let x, y be right and left eigenvectors corresponding to a simple finite eigenvalue λ of the pencil $\lambda E - A$. Let $\lambda E - (A + tBuv^H C)$ be a perturbed matrix pencil with eigenvalue $\tilde{\lambda}$. Then it holds

$$\tilde{\lambda} = \lambda + t \frac{y^H B u v^H C x}{y^H E x} + \mathcal{O}(t^2).$$

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Corollary

$$\left. \frac{d\tilde{\lambda}(t)}{dt} \right|_{t=0} = \frac{y^H B u v^H C x}{y^H E x}.$$

Construction of Structured Rank-1 Perturbations

Given:

- Pencil $\lambda E - A$ with simple eigenvalue λ , right/left eigenvectors x, y , $y^H E x > 0$;
- vectors $u \in \mathbb{C}^m, v \in \mathbb{C}^p$ with $\|u\|_2 = \|v\|_2 = 1$.

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$$\begin{aligned} \operatorname{Re} \left(\left. \frac{d\tilde{\lambda}(t)}{dt} \right|_{t=0} \right) &= \frac{\operatorname{Re} (y^H B u v^H C x)}{y^H E x} \\ &\leq \frac{\|y^H B\|_2 \|C x\|_2}{y^H E x}. \end{aligned}$$

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Equality holds for

$$u = \frac{B^T y}{\|B^T y\|_2}, \quad v = \frac{C x}{\|C x\|_2}.$$

Subsequent Steps

Given:

- Perturbed pencil $\lambda E - \hat{A} = \lambda E - (A + \varepsilon B \hat{u} \hat{v}^H C)$ with simple eigenvalue $\hat{\lambda}$, left/right eigenvectors \hat{x} , \hat{y} , $\hat{y}^H E \hat{x} > 0$;
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$$\lambda E - \left(\hat{A} + tB (uv^H - \hat{u}\hat{v}^H) C \right),$$

which is an ε -norm rank-1 perturbation of $\lambda E - A$ for $t = 0$, $t = \varepsilon$.

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Again, equality holds for

$$u = \frac{B^T \hat{y}}{\|B^T \hat{y}\|_2}, \quad v = \frac{C \hat{x}}{\|C \hat{x}\|_2}.$$

Choice of the Eigenvalues

We showed how to optimally perturb a chosen eigenvalue!

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⇒ **Subspace Accelerated MIMO Dominant Pole Algorithm (SAMDP)**

[ROMMES, MARTINS '06]

Dominant Poles

Assume that $\lambda E - A$ has only simple eigenvalues λ_k with left and right eigenvectors y_k and x_k such that $y_k^H E x_k = 1$. If $G(\cdot)$ is proper then

$$G(s) = C(sE - A)^{-1}B = \sum_{k=1}^n \frac{R_k}{s - \lambda_k} + R_\infty$$

with residues

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Observation: If λ_j is close to the imaginary axis and $\|R_j\|_2$ is large, then

$$G(i\omega) \approx \frac{R_j}{- \operatorname{Re}(\lambda_j)} + \sum_{\substack{k=1 \\ k \neq j}}^n \frac{R_k}{i\omega - \lambda_k} + R_\infty$$

for $\omega \approx \operatorname{Im}(\lambda_j)$ and therefore $\|G(i\omega)\|_2$ is large, too.

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for $\omega \approx \operatorname{Im}(\lambda_j)$ and therefore $\|G(i\omega)\|_2$ is large, too.

\implies Compute the **dominant poles** = λ_j with largest $\frac{\|R_j\|_2}{|\operatorname{Re}(\lambda_j)|}$!

Sketch of the Algorithm

Sketch of the algorithm

- 1 Choose dominant eigenvalue λ with right/left eigenvectors x, y .
- 2 Construct the perturbed pencil $\lambda E - \left(A + \varepsilon \frac{BB^T y x^H C^T C}{\|B^T y\|_2 \|Cx\|_2} \right)$.
- 3 Repeat Steps 1 and 2 until convergence.

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Remark

The dominant pole algorithm is also used to determine the initial ε !

Numerical Example – M20PI_n, $n = 1182$, $p = m = 3$

Phase 1: Searching initial pole:

1. inner iteration: $\text{psa} = -0.0679449$.
2. inner iteration: $\text{psa} = 0.00231404$.
3. inner iteration: $\text{psa} = 0.00302846$.
4. inner iteration: $\text{psa} = 0.00303551$.
5. inner iteration: $\text{psa} = 0.00303558$.

Iteration stagnates, pseudospectral abscissa found.

1. outer iteration: $\text{epsilon} = 0.25825$, $\text{psa} = 0.00303558$.

Phase 2: Iteration over epsilon:

1. inner iteration: $\text{psa} = 1.61449\text{e-}08$.
2. inner iteration: $\text{psa} = 1.62557\text{e-}08$.
3. inner iteration: $\text{psa} = 1.62568\text{e-}08$.

Iteration stagnates, pseudospectral abscissa found.

1. outer iteration: $\text{epsilon} = 0.258224$, $\text{psa} = 1.62568\text{e-}08$.

The H-infinity-norm is attained for $\text{fopt} = 5064.12$. The norm value is 3.8726.

The algorithm needed 2 outer and 8 inner iterations.

The runtime is 4.03271 seconds.

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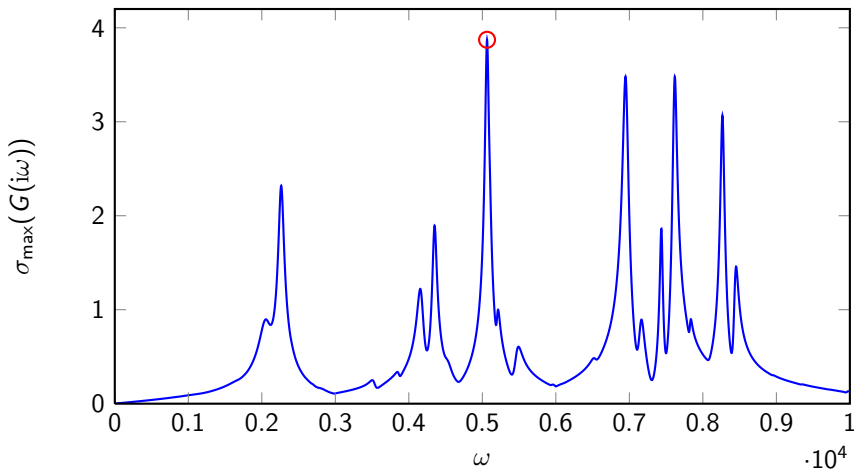


Figure: Transfer function plot with computed norm value

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\mathcal{H}_∞ -Norm and Even Matrix Pencils

Consider the even matrix pencil

$$\mathcal{H}_\gamma(\lambda) := \left[\begin{array}{cc|cc} 0 & -\lambda E^T - A^T & -C^T & 0 \\ \lambda E - A & 0 & 0 & -B \\ \hline -C & 0 & \gamma I_p & 0 \\ 0 & -B^T & 0 & \gamma I_m \end{array} \right].$$

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“Theorem”

Under some technical conditions, γ is a singular of $G(i\omega_0)$ if and only if $\mathcal{H}_\gamma(\lambda)$ has the eigenvalue $i\omega_0$.

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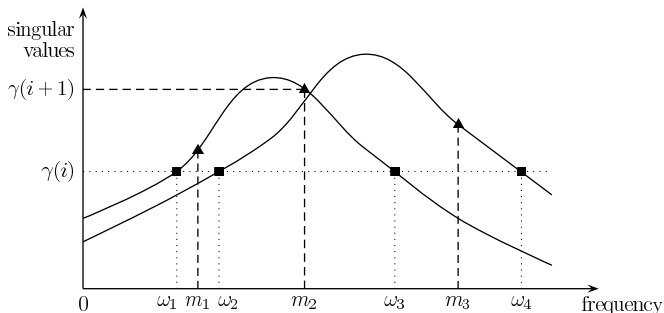
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“Theorem”

[BENNER, SIMA, V. '12]

let $\gamma > \min_{\omega \in \mathbb{R}} \sigma_{\max}(G(i\omega))$. Then, under some technical conditions $\|G\|_{\mathcal{H}_\infty} \geq \gamma$ if and only if $\mathcal{H}_\gamma(\lambda)$ has purely imaginary eigenvalues.

Algorithm Outline



General Algorithm

- ① Choose an initial value for γ .
- ② Determine purely imaginary eigenvalues of $\mathcal{H}_\gamma(\lambda)$.
- ③ If imaginary eigenvalues exist, increase γ and repeat Step 2.
- ④ If no imaginary eigenvalues exist, γ is an upper bound for $\|G\|_{\mathcal{H}_\infty}$.

Eigenvalue Computation

- Eigenvalues computed using the [structure-preserving](#) even IRA method.

[MEHRMANN, SCHRÖDER, SIMONCINI '12]

- Even IRA computes some eigenvalues close to a [prespecified shift](#).

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Problem:

- We need to determine [all](#) purely imaginary eigenvalues of $\mathcal{H}_\gamma(\lambda)$.
[This is an open problem!](#)
- **But:** Heuristically, the \mathcal{H}_∞ -norm is attained close to a dominant pole! \implies Use the imaginary parts of the dominant poles as shifts!

[LOWE, V. '13]

Numerical Example – M20PI_n, $n = 1182$, $p = m = 3$

The 6 most dominant poles with associated dominance values are:

- 28.763 + 5064.528i with dominance 3.714211
- 41.310 + 6951.137i with dominance 3.413362
- 32.264 + 7614.848i with dominance 3.376605
- 28.867 + 8266.724i with dominance 3.046229
- 36.085 + 11972.542i with dominance 2.313766
- 39.964 + 2263.478i with dominance 2.141803

The 6 most dominant poles are used to calculate the initial gamma value.

The initial lower bound of gamma is 3.872214 at $\text{fopt} = 5064.528178$.

For cycle 1:

The positive imaginary eigenvalues for shift = 5067.060442039i are:

$\lambda = 5063.711555996i$

$\lambda = 5064.524040687i$

There are 6 shifts, and 1 shifts that produce imaginary eigenvalues.

There are 24 eigenvalues, and 4 imaginary eigenvalues.

The lower bound of gamma is 3.872601 at $\text{fopt} = 5064.117782$.

For cycle 2:

There are 1 shifts, and 0 shifts that produce imaginary eigenvalues.

There are 4 eigenvalues, and 0 imaginary eigenvalues.

The L-infinity-norm is 3.8726 at $\text{fopt} = 5064.12$.

The runtime is 1.72567 seconds.

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Some More Timings

Table: Timings for some larger test examples

example	n	m	p	time in s	
				pseudospectra	even pencil
bips07_1693	13275	4	4	167.10	31.98
bips07_1998	15066	4	4	102.11	29.99
bips07_2476	16861	4	4	146.18	31.62
bips07_3078	21128	4	4	91.05	34.73
xingo_afonso_itaipu	13250	1	1	39.24	16.80
mimo8x8_system	13309	8	8	78.47	23.25
mimo28x28_system	13251	28	28	85.36	35.45
mimo46x46_system	13250	46	46	115.91	49.13

Comparison of the Methods

“Pseudospectra method”

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- slower than “even pencil method”
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“Even pencil method”

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- + works under less restrictive conditions than “pseudospectra method”
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- no guaranteed global optimization

- 1 Introduction
- 2 Method 1: Optimization over Structured Pseudospectra
- 3 Method 2: Optimization Using Even Matrix Pencils
- 4 Comparison
- 5 Summary and Open Questions

Summary and Open Questions

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Thanks for Listening!

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