

MATHICSE Technical Report

Nr. 32.2011

June 2011



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Generalized Eigenvalue Problems with Specified Eigenvalues

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June 22, 2011

Abstract

We consider the distance from a (square or rectangular) matrix pencil to the nearest matrix pencil in 2-norm that has a set of specified eigenvalues. We derive a singular value optimization characterization for this problem and illustrate its usefulness for two applications. First, the characterization yields a singular value formula for determining the nearest pencil whose eigenvalues lie in a specified region in the complex plane. For instance, this enables the numerical computation of the nearest stable descriptor system in control theory. Second, the characterization partially solves the problem posed in [Boutry et al. 2005] regarding the distance from a general rectangular pencil to the nearest pencil with a complete set of eigenvalues. The involved singular value optimization problems are solved by means of BFGS and Lipschitz-based global optimization algorithms.

Key words. Matrix pencils, eigenvalues, optimization of singular values, inverse eigenvalue problems, Lipschitz continuity.

AMS subject classifications. 65F15, 65F18, 90C26, 90C56

1 Introduction

Consider a matrix pencil $A - \lambda B$ where $A, B \in \mathbb{C}^{n \times m}$ with $n \geq m$. Then a scalar $\rho \in \mathbb{C}$ is called an *eigenvalue* of the pencil if there exists a nonzero vector $v \in \mathbb{C}^n$ such that

$$(A - \rho B)v = 0. \tag{1}$$

The vector v is said to be a (*right*) *eigenvector* associated with ρ and the pair (ρ, v) is said to be an *eigenpair* of the pencil.

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In the square case $m = n$, the eigenvalues are simply given by the roots of the characteristic polynomial $\det(A - \lambda B)$ and there are usually n eigenvalues, counting multiplicities. The situation is quite the opposite for $n > m$. Generically, a rectangular pencil $A - \lambda B$ has no eigenvalues at all. To see this, notice that a necessary condition for the satisfaction of (1) is that $n!/((n-m)!m!)$ polynomials, each corresponding to the determinant of a pencil obtained by choosing m rows of $A - \lambda B$ out of n rows, must have a common root. Also, the generic Kronecker canonical form of a rectangular matrix pencil only consists of singular blocks [7]. Hence, (1) is an ill-posed problem and requires reformulation before admitting numerical treatment.

To motivate our reformulation of (1), we describe a typical situation giving rise to rectangular matrix pencils. Let $M \in \mathbb{C}^{n \times n}$ and suppose that the columns of $U \in \mathbb{C}^{n \times m}$ form an orthonormal basis for a subspace $\mathcal{U} \subset \mathbb{C}^n$ known to contain approximations to some eigenvectors of M . Then it is quite natural to consider the $n \times m$ matrix pencil

$$A - \lambda B := MU - \lambda U. \quad (2)$$

The approximations contained in U and the approximate eigenpairs of $A - \lambda B$ are closely connected to each other. In one direction, suppose that (ρ, x) with $x \in \mathcal{U}$ satisfies

$$(M + \Delta M - \rho I)x = 0 \quad (3)$$

for some (small) perturbation ΔM . Then there is $v \in \mathbb{C}^n$ such that $x = Uv$. Moreover, we have

$$(A + \Delta A - \rho B)v = 0 \quad (4)$$

with $\Delta A := \Delta M \cdot U$ satisfying $\|\Delta A\|_2 \leq \|\Delta M\|_2$. In the other direction, the relation (4) with an arbitrary ΔA implies (3) with $\Delta M = \Delta A \cdot U^*$ satisfying $\|\Delta M\|_2 = \|\Delta A\|_2$. Unless M is normal, the first part of this equivalence between approximate eigenpairs of M and $A - \lambda B$ does not hold when the latter is replaced by the more common compression U^*MU . This observation has led to the use of rectangular matrix pencils in, e.g., large-scale pseudospectra computation [28] and Ritz vector extraction [15].

This paper is concerned with determining the 2-norm distance from the pencil $A - \lambda B$ to the nearest pencil $(A + \Delta A) - \lambda B$ with a subset of specified eigenvalues. To be precise, let $\mathbb{S} = \{\lambda_1, \dots, \lambda_k\}$ be a set of distinct complex numbers and let r be a positive integer. Let $m_j(A + \Delta A, B)$ denote the (possibly zero) algebraic multiplicity¹ of λ_j as an eigenvalue of $(A + \Delta A) - \lambda B$. Then we consider the distance

$$\tau_r(\mathbb{S}) := \inf \left\{ \|\Delta A\|_2 : \sum_{j=1}^k m_j(A + \Delta A, B) \geq r \right\}. \quad (5)$$

For $k = r = 1$, it is relatively easy to see that

$$\tau_1(\{\lambda_1\}) = \sigma_m(A - \lambda_1 B),$$

¹For a rectangular matrix pencil, the algebraic multiplicity of λ_j is defined as the sum of the sizes of associated regular Jordan blocks in the Kronecker canonical form, see also Section 2. By definition, this number is zero if λ_j is actually not an eigenvalue of the pencil.

where, here and in the following, σ_k denotes the k th largest singular value of a matrix. One of the main contributions of this paper is a derivation of a similar singular value optimization characterization for general k and r , which facilitates the computation of $\tau_r(\mathbb{S})$. Very little seems to be known in this direction. Existing results concern the square matrix case ($m = n$ and $B = I$); see the works by Malyshev [21] for $k = 1$ and $r = 2$ as well as Lippert [18] for $k = 2$ and $r = 2$, Ikramov et al. [13] for $k = 1$ and $r = 3$, and Mengi [22] for general $k = 1$ and arbitrary r . Some attempts have also been made by Lippert [19] for arbitrary k and r and for the square matrix case, and by Pappathanasiou et al. [24] for $k = 1$ and $r = 2$ and for the square matrix polynomial case.

Another class of applications arises in (robust) control theory, where a number of tasks require the determination of a (minimal) perturbation that moves some or all eigenvalues into a certain region in the complex plane. With the region of interest denoted by $\Omega \subseteq \mathbb{C}$, the results in this paper are an important step towards rendering the numerical computation of the distance

$$\begin{aligned} \tau_r(\Omega) &:= \inf \{ \|\Delta A\|_2 : (A + \Delta A) - \lambda B \text{ has } r \text{ finite eigenvalues in } \Omega \} \\ &= \inf_{\mathbb{S} \subseteq \Omega} \tau_r(\mathbb{S}) \end{aligned}$$

feasible. Here and in the following, multiple eigenvalues are counted according to their algebraic multiplicities. For $r = 1$ and Ω equal to \mathbb{C}^+ (right-half complex plane), the quantity $\tau_1(\mathbb{C}^+)$ amounts to the distance to instability, also called stability radius. In [29], a singular value characterization of $\tau_1(\mathbb{C}^+)$ was provided, forming the basis of a number of algorithms for computing $\tau_1(\mathbb{C}^+)$, see, e.g., [3, 6]. In our more general setting, we can also address the converse question: Given an unstable matrix pencil $A - \lambda B$, determine the closest stable pencil. Notice that this problem is intrinsically harder than the distance to instability. For the distance to instability it suffices to perturb the system so that *one of the eigenvalues* is in the undesired region. On the other hand to make an unstable system stable one needs to perturb the system so that *all eigenvalues* lie in the region of stability.

An important special case, $\Omega = \mathbb{C}$ leads to

$$\begin{aligned} \tau_r(\mathbb{C}) &:= \inf \{ \|\Delta A\|_2 : (A + \Delta A) - \lambda B \text{ has } r \text{ finite eigenvalues} \} \\ &= \inf_{\mathbb{S} \subseteq \mathbb{C}} \tau_r(\mathbb{S}). \end{aligned}$$

For $r = 1$ and particular choices of A and B , the distance $\tau_1(\mathbb{C})$ corresponds to the distance to uncontrollability for a matrix pair [5, 8]. For general r , a variant of this distance was suggested in [2] to solve an inverse signal processing problem approximately. More specifically, this problem is concerned with the identification of the shape of a region in the complex plane given the moments over the region. If the region is assumed to be a polygon, then its vertices can be posed as the eigenvalues of a rectangular pencil $A - \lambda B$, where A and B are not exact due to measurement errors, causing the pencil to have no eigenvalues [9]. Then the authors attempt to locate nearby pencils with a complete set of eigenvalues.

The outline of this paper is as follows. In the next section, we review the Kronecker canonical form for the pencil $A - \lambda B$. In §3, we derive a rank characterization for the condition $\sum_{j=1}^k m_j(A, B) \geq r$. This is a crucial prerequisite for deriving the singular value characterizations of $\tau_r(\mathbb{S})$ in §4. We discuss several corollaries of the singular value characterizations

for $\tau_r(\mathbb{S})$, in particular for $\tau_r(\Omega)$ and $\tau_r(\mathbb{C})$, in §5. The singular value characterizations are deduced under certain mild multiplicity and linear independence assumptions. Although we expect these assumptions to be satisfied for examples of practical interest, they may fail to hold as demonstrated by two academic examples in §6. Interestingly, the singular value characterization remains true for these examples despite the fact that our derivation no longer applies. Finally, a numerical approach to solving the involved singular value optimization problems is briefly outlined in §7 and applied to a number of settings in §8. The main point of the developed numerical method and the experiments is to demonstrate that the singular value characterizations facilitate the computation of $\tau_r(\mathcal{S})$, $\tau_r(\omega)$ and $\tau_r(\mathbb{C})$. We do not claim that the method outlined here is as efficient as it could be, neither do we claim that it is reliable.

2 Kronecker Canonical Form

Given a matrix pencil $A - \lambda B \in \mathbb{C}^{n \times m}$, the Kronecker canonical form (KCF), see [11], states the existence of invertible matrices $P \in \mathbb{C}^{n \times n}$ and $Q \in \mathbb{C}^{m \times m}$ such that the transformed pencil $P(A - \lambda B)Q$ is block diagonal with each diagonal block taking the form

$$J_p(\alpha) - \lambda I_p \quad \text{or} \quad I_p - \lambda J_p(0) \quad \text{or} \quad F_p - \lambda G_p \quad \text{or} \quad F_p^T - \lambda G_p^T,$$

where

$$J_p(\alpha) = \underbrace{\begin{bmatrix} \alpha & 1 & & \\ & \alpha & \ddots & \\ & & \ddots & 1 \\ & & & \alpha \end{bmatrix}}_{p \times p}, \quad F_p = \underbrace{\begin{bmatrix} 1 & 0 & & \\ & \ddots & \ddots & \\ & & 1 & 0 \end{bmatrix}}_{p \times (p+1)}, \quad G_p = \underbrace{\begin{bmatrix} 0 & 1 & & \\ & \ddots & \ddots & \\ & & 0 & 1 \end{bmatrix}}_{p \times (p+1)} \quad (6)$$

for some $\alpha \in \mathbb{C}$. *Regular blocks* take the form $J_p(\alpha) - \lambda I_p$ or $I_p - \lambda J_p(0)$, with $p \geq 1$, corresponding to finite or infinite eigenvalues, respectively. *Singular blocks* take the form $F_p - \lambda G_p$ or $F_p^T - \lambda G_p^T$, with $p \geq 0$, and correspond to so called Kronecker indices.

In large parts of this paper, indeed until the main singular value optimization characterization, we will assume that B has full column rank. (This assumption will not be needed for the singular value optimization characterization due to the continuity of singular values and the distance $\tau_r(\mathbb{S})$.) Clearly, this assumption rules out the occurrence of singular blocks of the type $F_p - \lambda G_p$.

3 Rank Characterization for Pencils with Specified Eigenvalues

In this section we derive a rank characterization for the satisfaction of the condition

$$\sum_{j=1}^k m_j(A, B) \geq r, \quad (7)$$

where $m_j(A, B)$ denotes the algebraic multiplicity of the eigenvalue λ_j . The following classical result [11, Theorem 1, p. 219] concerning the dimension of the solution space for a Sylvester equation will play a central role.

Theorem 3.1. *Let $F \in \mathbb{C}^{m \times m}$ and $G \in \mathbb{C}^{r \times r}$. Then the dimension of the solution space for the Sylvester equation*

$$FX - XG = 0$$

only depends on the Jordan canonical forms of the matrices F and G . Specifically, suppose that μ_1, \dots, μ_ℓ are the common eigenvalues of F and G . Let $c_{j,1}, \dots, c_{j,\ell_j}$ and $p_{j,1}, \dots, p_{j,\tilde{\ell}_j}$ denote the sizes of the Jordan blocks of F and G associated with the eigenvalue μ_j , respectively. Then

$$\dim\{X \in \mathbb{C}^{m \times r} : FX - XG = 0\} = \sum_{j=1}^{\ell} \sum_{i=1}^{\ell_j} \sum_{q=1}^{\tilde{\ell}_j} \min(c_{j,i}, p_{j,q}).$$

For our purposes, we need to extend the result of Theorem 3.1 to a generalized Sylvester equation of the form

$$AX - BXC = 0, \quad (8)$$

where C is a matrix with the desired set of eigenvalues \mathbb{S} and with correct algebraic multiplicities. When assuming that B has full column rank, this extension becomes rather straightforward.² To see this, let us partition the KCF

$$P(A - \lambda B)Q = \text{diag}(A_F - \lambda I, I - \lambda A_I, A_S - \lambda B_S), \quad (9)$$

such that

- $A_F - \lambda I$ contains all regular blocks corresponding to finite eigenvalues;
- $I - \lambda A_I$ contains all regular blocks corresponding to infinite eigenvalues;
- $A_S - \lambda B_S$ contains all singular blocks of the form $F_p^T - \lambda G_p^T$.

Note that the finite eigenvalues of $A - \lambda B$ equal the eigenvalues of A_F with the same algebraic and geometric multiplicities.

Using (9), X is a solution of the generalized Sylvester equation (8) if and only if

$$(PAQ)(Q^{-1}X) - (PBQ)(Q^{-1}X)C = 0 \iff \text{diag}(A_F, I, A_S)Y - \text{diag}(I, A_I, B_S)YC = 0$$

where $Y = Q^{-1}X$. Consequently, the dimension of the solution space for (8) is the sum of the solution space dimensions of the equations

$$A_F X - XC = 0, \quad X - A_I X C = 0 \quad \text{and} \quad A_S X - B_S X C = 0.$$

Taking the structures of A_I and A_S, B_S into account, it can be directly seen that the latter two equations only admit the trivial solution $X = 0$. To summarize: the solution spaces of the generalized Sylvester equation (8) and the (standard) Sylvester equation

$$A_F X - XC = 0$$

have the same dimension. Applying Theorem 3.1 we therefore obtain the following result.

²Košir [17] provides an extension of Theorem 3.1 to an even more general setting.

Theorem 3.2. *Let $A, B \in \mathbb{C}^{n \times m}$ be such that $n \geq m$ and $\text{rank}(B) = m$, and $C \in \mathbb{C}^{r \times r}$. Then the dimension of the solution space for the generalized Sylvester equation*

$$AX - BXC = 0$$

only depends on the Kronecker canonical form of $A - \lambda B$ and the Jordan canonical form of C . Specifically suppose that μ_1, \dots, μ_ℓ are the common eigenvalues of $A - \lambda B$ and C . Let $c_{j,1}, \dots, c_{j,\ell_j}$ and $p_{j,1}, \dots, p_{j,\tilde{\ell}_j}$ denote the sizes of the Jordan blocks of $A - \lambda B$ and C associated with the eigenvalue μ_j , respectively. Then

$$\dim\{X \in \mathbb{C}^{m \times r} : AX - BXC = 0\} = \sum_{j=1}^{\ell} \sum_{i=1}^{\ell_j} \sum_{q=1}^{\tilde{\ell}_j} \min(c_{j,i}, p_{j,q}).$$

We now apply the result of Theorem 3.2 to the generalized Sylvester equation

$$AX - BXC(\mu, \Gamma) = 0, \quad (10)$$

where $C(\mu, \Gamma)$ takes the form

$$C(\mu, \Gamma) = \begin{bmatrix} \mu_1 & -\gamma_{21} & \cdots & -\gamma_{r1} \\ 0 & \mu_2 & \ddots & \vdots \\ & & \ddots & -\gamma_{r,r-1} \\ 0 & & & \mu_r \end{bmatrix}, \quad (11)$$

with

$$\mu = [\mu_1 \ \mu_2 \ \cdots \ \mu_r]^T \in \mathbb{S}^r, \quad \Gamma = [\gamma_{21} \ \gamma_{31} \ \cdots \ \gamma_{r,r-1}]^T \in \mathbb{C}^{r(r-1)/2}.$$

As explained in the introduction, the set $\mathbb{S} = \{\lambda_1, \dots, \lambda_k\}$ contains desired approximate eigenvalues. Suppose λ_j occurs p_j times in μ . Furthermore, as in Theorem 3.2, denote the sizes of the Jordan blocks of $A - \lambda B$ and $C(\mu, \Gamma)$ associated with the scalar λ_j by $c_{j,1}, \dots, c_{j,\ell_j}$ and $p_{j,1}, \dots, p_{j,\tilde{\ell}_j}$, respectively. Note that $p_j = \sum_{q=1}^{\tilde{\ell}_j} p_{j,q}$. In fact, for generic values of Γ the matrix $C(\mu, \Gamma)$ has at most one Jordan block of size p_j associated with λ_j for $j = 1, \dots, k$, see [7]. In the following, we denote this set of generic values for Γ by \mathcal{G} .

First, suppose that inequality (7) holds. If we choose μ such that $p_j \leq m_j(A, B) = \sum_{i=1}^{\ell_j} c_{j,i}$, then Theorem 3.2 implies that the dimension of the solution space for the generalized Sylvester equation (10) is

$$\sum_{j=1}^k \sum_{i=1}^{\ell_j} \sum_{q=1}^{\tilde{\ell}_j} \min(c_{j,i}, p_{j,q}) \geq \sum_{j=1}^k \sum_{i=1}^{\ell_j} \min(c_{j,i}, p_j) \geq \sum_{j=1}^k \min(m_j(A, B), p_j) = \sum_{j=1}^k p_j = r.$$

In other words, there exists a vector μ with components from \mathbb{S} such that the dimension of the solution space of the Sylvester equation (10) is at least r .

Now, on the contrary, suppose that inequality (7) does not hold. Then for generic values of $\Gamma \in \mathcal{G}$, the solution space dimension of (10) is

$$\sum_{j=1}^k \sum_{i=1}^{\ell_j} \min(c_{j,i}, p_j) \leq \sum_{j=1}^k \sum_{i=1}^{\ell_j} c_{j,i} = \sum_{j=1}^k m_j(A, B) < r.$$

Lemma 4.1. Consider $C \in \mathbb{C}^{\ell \times q}$ and a positive integer $p < \min(\ell, q)$. Then

$$\inf \{ \|\Delta C\|_2 : \text{rank}(C + \Delta C) \leq p \} = \sigma_{p+1}(C).$$

Defining

$$\mathcal{P}_r(\mu) := \inf \{ \|\Delta A\|_2 : \text{rank}(\mathcal{L}(\mu, \Gamma, A + \Delta A, B)) \leq mr - r \}$$

for some $\Gamma \in \mathcal{G}$, Corollary 3.4 implies

$$\tau_r(\mathbb{S}) = \inf_{\mu \in \mathbb{S}^r} \mathcal{P}_r(\mu),$$

independent of the choice of Γ . By Lemma 4.1, it holds that

$$\begin{aligned} \mathcal{P}_r(\mu) &= \inf \{ \|\Delta A\|_2 : \text{rank}(\mathcal{L}(\mu, \Gamma, A + \Delta A, B)) \leq mr - r \} \\ &\geq \sigma_{mr-r+1}(\mathcal{L}(\mu, \Gamma, A, B)), \end{aligned}$$

using the fact that A enters \mathcal{L} linearly. Note that this inequality in general is *not* an equality due to the fact that the allowable perturbations to $\mathcal{L}(\mu, \Gamma, A, B)$ in the definition of $\mathcal{P}_r(\mu)$ do not respect the structure of the matrix. On the other hand, the inequality holds for all $\Gamma \in \mathcal{G}$ and hence – by continuity of the singular value $\sigma_{mr-r+1}(\cdot)$ with respect to Γ – we obtain the lower bound

$$\mathcal{P}_r(\mu) \geq \sup_{\Gamma \in \mathbb{C}^{r(r-1)/2}} \sigma_{mr-r+1}(\mathcal{L}(\mu, \Gamma, A, B)) =: \kappa_r(\mu). \quad (13)$$

From the fact that $\sigma_{mr-r+1}(\mathcal{L}(\mu, \Gamma_*, A, B))$ tends to zero as $\|\Gamma\| := \sum |\gamma_{ij}|^2 \rightarrow \infty$ (which can be shown analogously as in [14, §5]) and the continuity of singular values, it follows that the supremum is attained at some Γ_* :

$$\kappa_r(\mu) = \sigma_{mr-r+1}(\mathcal{L}(\mu, \Gamma_*, A, B)).$$

Throughout the rest of this section we assume that $\Gamma_* \in \mathcal{G}$.

We will establish the reverse inequality $\mathcal{P}_r(\mu) \leq \kappa_r(\mu)$ by constructing an optimal perturbation ΔA_* such that

- (i) $\|\Delta A_*\|_2 = \kappa_r(\mu)$, and
- (ii) $\text{rank}(\mathcal{L}(\mu, \Gamma_*, A + \Delta A_*, B)) \leq mr - r$.

Let us consider the left and right singular vectors $U \in \mathbb{C}^{rn}$ and $V \in \mathbb{C}^{rm}$ satisfying the relations

$$\mathcal{L}(\mu, \Gamma_*, A, B) V = \kappa_r(\mu) U, \quad U^* \mathcal{L}(\mu, \Gamma_*, A, B) = V^* \kappa_r(\mu), \quad \|U\|_2 = \|V\|_2 = 1. \quad (14)$$

The aim of the next two subsections is to show that the perturbation

$$\Delta A_* := -\kappa_r(\mu) \mathcal{U} \mathcal{V}^+ \quad (15)$$

with $\mathcal{U} \in \mathbb{C}^{n \times r}$ and $\mathcal{V} \in \mathbb{C}^{m \times r}$ such that $\text{vec}(\mathcal{U}) = U$ and $\text{vec}(\mathcal{V}) = V$ satisfies properties (i) and (ii). Here, \mathcal{V}^+ denotes the Moore-Penrose pseudoinverse of \mathcal{V} . The optimality of ΔA_* will be established under the following additional assumptions.

Definition 4.2 (Multiplicity Qualification). *We say that the multiplicity qualification holds at (μ, Γ) for the pencil $A - \lambda B$ if the multiplicity of the singular value $\sigma_{mr-r+1}(\mathcal{L}(\mu, \Gamma, A, B))$ is one.*

Definition 4.3 (Linear Independence Qualification). *We say that the linear independence qualification holds at (μ, Γ) for the pencil $A - \lambda B$ if there is a right singular vector V associated with $\sigma_{mr-r+1}(\mathcal{L}(\mu, \Gamma, A, B))$ such that $\mathcal{V} \in \mathbb{C}^{m \times r}$, with $\text{vec}(\mathcal{V}) = V$, has full column rank.*

Definition 4.4 (Full Jordan Block Qualification). *We say that the full Jordan block qualification holds at (μ, Γ) if the geometric multiplicities of all eigenvalues of $C(\mu, \Gamma)$ are one.*

Note that Definition 4.4 amounts to requiring $\Gamma \in \mathcal{G}$.

4.1 The 2-norm of the optimal perturbation

Throughout this section we assume that the multiplicity qualification holds at the optimal (μ, Γ_*) for the pencil $A - \lambda B$. Moreover, we can restrict ourselves to the case $\kappa_r(\mu) \neq 0$, as the optimal perturbation is trivially given by $\Delta A_* = 0$ when $\kappa_r(\mu) = 0$.

Let $\mathcal{A}(\gamma)$ be a matrix-valued function depending analytically on a parameter $\gamma \in \mathbb{R}$. If the multiplicity of $\sigma_j(\mathcal{A}(\gamma_*))$ is one and $\sigma_j(\mathcal{A}(\gamma_*)) \neq 0$ then $\sigma_j(\mathcal{A}(\gamma))$ is analytic at $\gamma = \gamma_*$, with the derivative

$$\frac{\partial \sigma_j(\mathcal{A}(\gamma_*))}{\partial \gamma} = \text{Re} \left(u_j^* \frac{\partial \mathcal{A}(\gamma_*)}{\partial \gamma} v_j \right), \quad (16)$$

where u_j and v_j denote a consistent pair of unit left and right singular vectors associated with $\sigma_j(\mathcal{A}(\gamma_*))$, see, e.g., [4, 21, 26].

Let us now define

$$f(\Gamma) := \sigma_{nr-r+1}(\mathcal{L}(\mu, \Gamma, A, B)),$$

where we view f as a mapping $\mathbb{R}^{r(r-1)} \rightarrow \mathbb{R}$ by decomposing each complex parameter $\gamma_{j\ell}$ contained in Γ into its real and imaginary parts $\Re \gamma_{j\ell}$ and $\Im \gamma_{j\ell}$. By (16), we have

$$\frac{\partial f(\Gamma_*)}{\partial \Re \gamma_{j\ell}} = \text{Re}(U_j^* B V_\ell), \quad \frac{\partial f(\Gamma_*)}{\partial \Im \gamma_{j\ell}} = \text{Re}(i U_j^* B V_\ell) = -\text{Im}(U_j^* B V_\ell),$$

where $U_j \in \mathbb{C}^n$ and $V_\ell \in \mathbb{C}^m$ denote the j th and ℓ th block components of U and V , respectively. Furthermore, the fact that Γ_* is a global maximizer of f implies that both derivatives are zero. Consequently we obtain the following result.

Lemma 4.5. *Suppose that the multiplicity qualification holds at (μ, Γ_*) for the pencil $A - \lambda B$ and $\kappa_r(\mu) \neq 0$. Then $U_j^* B V_\ell = 0$ for all $j = 2, \dots, r$ and $\ell = 1, \dots, j-1$.*

Now by exploiting Lemma 4.5 we show $\mathcal{U}^* \mathcal{U} = \mathcal{V}^* \mathcal{V}$. Geometrically this means that the angle between U_i and U_j is identical with the angle between V_i and V_j .

Lemma 4.6. *Under the assumptions of Lemma 4.5 it holds that $\mathcal{U}^* \mathcal{U} = \mathcal{V}^* \mathcal{V}$.*

Proof. To show the desired result, we need to establish the equality $U_j^* U_\ell = V_j^* V_\ell$ for all $j = 1, \dots, r$ and $\ell = 1, \dots, j$. For any such pair j, ℓ , the singular vector relation (14) implies

$$U_j^*(A - \mu_j B) + U_{j+1}^* B \gamma_{j+1,j} + U_{j+2}^* B \gamma_{j+2,j} + \dots + U_r^* B \gamma_{rj} = \kappa_r(\mu) V_j^* \quad (17)$$

and

$$B\gamma_{\ell 1}V_1 + B\gamma_{\ell 2}V_2 + \cdots + B\gamma_{\ell(\ell-1)}V_{\ell-1} + (A - \mu_\ell B)V_\ell = \kappa_r(\mu)U_\ell. \quad (18)$$

Multiplying (18) with U_j^* from the left, we obtain

$$U_j^*B\gamma_{\ell 1}V_1 + \cdots + U_j^*B\gamma_{\ell(\ell-1)}V_{\ell-1} + U_j^*(A - \mu_\ell B)V_\ell = U_j^*(A - \mu_\ell B)V_\ell = \kappa_r(\mu)U_j^*U_\ell,$$

where the first equality follows from Lemma 4.5. By the same lemma, $U_j^*(\mu_j - \mu_\ell)BV_\ell = 0$ for $\ell < j$ and the above equality can therefore be rewritten as

$$U_j^*(A - \mu_j B)V_\ell = \kappa_r(\mu)U_j^*U_\ell.$$

Analogously, (17) implies $U_j^*(A - \mu_j B)V_\ell = \kappa_r(\mu)V_j^*V_\ell$, which – when combined with the previous equality – gives

$$\kappa_r(\mu)V_j^*V_\ell = \kappa_r(\mu)U_j^*U_\ell.$$

Combined with $\kappa_r(\mu) \neq 0$, this concludes the proof. \square

The result of Lemma 4.6 implies $\|\mathcal{U}\mathcal{V}^+\|_2 = 1$. A formal proof of this implication can be found in [21, Lemma 2] and [22, Theorem 2.5]. Indeed, the equality $\|\mathcal{U}\mathcal{V}^+\|_2 = 1$ can be directly deduced from $\|\mathcal{U}\mathcal{V}^+x\|_2 = \|\mathcal{V}\mathcal{V}^+x\|_2$ for every x (implied by Lemma 4.6), and $\|\mathcal{V}\mathcal{V}^+\|_2 = 1$ (since $\mathcal{V}\mathcal{V}^+$ is an orthogonal projector).

Theorem 4.7. *Suppose that the multiplicity qualification holds at (μ, Γ_*) for the pencil $A - \lambda B$. Then the perturbation ΔA_* defined in (15) satisfies $\|\Delta A_*\|_2 = \kappa_r(\mu)$.*

4.2 Satisfaction of the rank condition by the optimally perturbed pencil

Now we assume that the linear independence qualification (Definition 4.3) holds at (μ, Γ_*) for the pencil $A - \lambda B$. In particular we can choose a right singular “vector” $\text{vec}(\mathcal{V})$ so that \mathcal{V} has full column rank. We will establish that

$$\text{rank}(\mathcal{L}(\mu, \Gamma_*, A + \Delta A_*, B)) \leq mr - r \quad (19)$$

for ΔA_* defined as in (15).

Writing the first part of the singular vector characterization (14) in matrix form leads to the generalized Sylvester equation

$$A\mathcal{V} - B\mathcal{V}C(\mu, \Gamma_*) = \kappa_r(\mu)\mathcal{U}.$$

The fact that \mathcal{V} has full column rank implies $\mathcal{V}^+\mathcal{V} = I$ and hence

$$\begin{aligned} A\mathcal{V} - B\mathcal{V}C(\mu, \Gamma_*) &= \kappa_r(\mu)\mathcal{U}\mathcal{V}^+\mathcal{V} \\ \implies (A - \kappa_r(\mu)\mathcal{U}\mathcal{V}^+)\mathcal{V} - B\mathcal{V}C(\mu, \Gamma_*) &= 0 \\ \implies (A + \Delta A_*)\mathcal{V} - B\mathcal{V}C(\mu, \Gamma_*) &= 0. \end{aligned}$$

Let us consider $\mathcal{M} = \{D \in \mathbb{C}^{r \times r} : C(\mu, \Gamma_*)D - DC(\mu, \Gamma_*) = 0\}$, the subspace of all $r \times r$ matrices commuting with $C(\mu, \Gamma_*)$. By Theorem 3.2, \mathcal{M} is a subspace of dimension at least r . Clearly for all $D \in \mathcal{M}$, we have

$$0 = (A + \Delta A_*)\mathcal{V}D - B\mathcal{V}C(\mu, \Gamma_*)D = (A + \Delta A_*)(\mathcal{V}D) - B(\mathcal{V}D)C(\mu, \Gamma_*).$$

In other words, $\{\mathcal{V}D : D \in \mathcal{M}\}$ has dimension at least r (using the fact that \mathcal{V} has full column rank) and represents a subspace of solutions to the generalized Sylvester equation

$$(A + \Delta A_*)X - BXC(\mu, \Gamma_*) = 0.$$

Reinterpreting this result in terms of the matrix representation, the desired rank estimate (19) follows.

This completes the derivation of $\mathcal{P}_r(\mu) \leq \kappa_r(\mu)$ under the stated assumptions. We conclude this section with a summary of the obtained singular value optimization characterization.

Theorem 4.8 (Nearest Pencils with Specified Eigenvalues). *Let $A - \lambda B$ be an $n \times m$ pencil with $n \geq m$, let r be a positive integer and let $\mathbb{S} = \{\lambda_1, \dots, \lambda_k\}$ be a set of distinct complex scalars.*

(i) *Then*

$$\tau_r(\mathbb{S}) = \inf_{\mu \in \mathbb{S}^r} \sup_{\Gamma} \sigma_{mr-r+1}(\mathcal{L}(\mu, \Gamma, A, B))$$

holds, provided that the optimization problem on the right is attained at some (μ_, Γ_*) for which the multiplicity, linear independence and full Jordan block qualifications hold.*

(ii) *A minimal perturbation ΔA_* such that $\sum_{j=1}^k m(A + \Delta A_*, B) \geq r$ is given by (15), with μ replaced by μ_* .*

Notice that Theorem 4.8 does not require B to have full column rank. This is justified because both the distance $\tau_r(\mathbb{S})$ and the singular value characterization change continuously with respect to B . More specifically, suppose that B does not have full column rank. Then there is an arbitrarily small perturbation ΔB such that $B + \Delta B$ has full column rank. Consequently, by letting $\Delta B \rightarrow 0$, the singular value characterization also holds in the rank-deficient case.

5 Corollaries of Theorem 4.8

As discussed in the introduction one potential application of Theorem 4.8 is in control theory, to ensure that the eigenvalues lie in a particular region in the complex plane. Thus let Ω be a subset of the complex plane. Then, provided that the assumptions of Theorem 4.8 hold, we have the following singular value characterization for the distance to the nearest pencil with r eigenvalues in Ω :

$$\begin{aligned} \tau_r(\Omega) &:= \inf_{\mathbb{S} \subseteq \Omega} \tau_r(\mathbb{S}) \\ &= \inf_{\mathbb{S} \subseteq \Omega} \inf_{\mu \in \mathbb{S}^r} \sup_{\Gamma} \sigma_{mr-r+1}(\mathcal{L}(\mu, \Gamma, A, B)) \\ &= \inf_{\mu \in \Omega^r} \sup_{\Gamma} \sigma_{mr-r+1}(\mathcal{L}(\mu, \Gamma, A, B)), \end{aligned} \tag{20}$$

where Ω^r denotes the set of vectors of length r with all entries in Ω .

When the pencil $A - \lambda B$ is rectangular, that is $n > m$, the pencil has generically no eigenvalues. Then the distance to the nearest rectangular pencil with r eigenvalues is of interest. In this case, the singular value characterization takes the following form:

$$\tau_r(\mathbb{C}) = \inf_{\mu \in \mathbb{C}^r} \sup_{\Gamma} \sigma_{mr-r+1}(\mathcal{L}(\mu, \Gamma, A, B)). \quad (21)$$

The optimal perturbations ΔA_* such that the pencil $(A + \Delta A_*) - \lambda B$ has eigenvalues (in \mathbb{C} and Ω) are given by (15), with μ replaced by the minimizing μ values in (21) and (20), respectively.

6 Multiplicity and linear independence qualifications

The results in this paper are proved under the assumptions of multiplicity, linear independence and full Jordan block qualifications. This section provides examples for which the multiplicity and linear independence qualifications are not satisfied for all values of Γ . Note that this does not mean that these assumptions are necessary to prove the results from this paper. In fact, numerical experiments suggest that our results may hold even if these assumptions are not satisfied.

As a first example, consider the pencil

$$\begin{bmatrix} 0 & -2 \\ -4 \sin \varphi & 0 \\ 4 \cos \varphi & 0 \end{bmatrix} - \lambda \begin{bmatrix} 1 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix},$$

where φ is an arbitrary real number. Let $\mu = [0 \ -2]^T$, that is, the target eigenvalues are 0 and -2 . Then for all γ the right singular vector associated with $\sigma_3(\mathcal{L}(\mu, \gamma, A, B)) = 2$ is given by $V = [0 \ 1 \ 0 \ 0]^T$, which clearly has linearly dependent components. Note that the multiplicity qualification holds.

As a second example, consider the pencil

$$\begin{bmatrix} 0 & -2 \\ -2 \sin \varphi & 0 \\ 2 \cos \varphi & 0 \end{bmatrix} - \lambda \begin{bmatrix} 1 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix},$$

where, again, φ is an arbitrary real number and $\mu = [0 \ -2]^T$. Then the singular value $\sigma_3(\mathcal{L}(\mu, \gamma, A, B)) = 2$ has multiplicity 2 for all $\gamma \in \mathbb{C}$. Moreover, the linear independence qualification also fails to hold.

In both examples it can be shown that the perturbation provided by (15) is optimal.

7 Computational issues

A numerical technique that can be used to compute $\tau_r(\Omega)$ and $\tau_r(\mathbb{C})$ based on the singular value characterizations was already described in [22, 23]. For completeness, we briefly recall this technique in the following. The distances of interest can be characterized as

$$\tau_r(\Omega) = \inf_{\mu \in \Omega^r} g(\mu) \quad \text{and} \quad \tau_r(\mathbb{C}) = \inf_{\mu \in \mathbb{C}^r} g(\mu),$$

where $g : \mathbb{C}^r \rightarrow \mathbb{R}$ is defined by

$$g(\mu) := \sup_{\Gamma \in \mathbb{C}^{r(r-1)/2}} \sigma_{mr-r+1}(\mathcal{L}(\mu, \Gamma, A, B)).$$

The inner maximization problems are solved by BFGS, even though $\sigma_{mr-r+1}(\cdot)$ is not differentiable at multiple singular values. In practice this is not a major issue for BFGS, as the multiplicity of the r th smallest singular value is generically one for all Γ for any given μ . If the multiplicity, linear independence and full Jordan block qualifications hold at a local maximizer Γ_* , then Γ_* is in fact a global maximizer and hence $g(\mu)$ is retrieved. If, on the other hand, BFGS converges to a point where one of these qualifications is violated, it needs to be restarted with a different initial guess. In practice we have almost always observed convergence to a global maximizer immediately, without the need for such a restart.

Although the function $g(\mu)$ is in general non-convex, it is Lipschitz continuous:

$$|g(\mu + \delta\mu) - g(\mu)| \leq \|\delta\mu\|_2.$$

There are various Lipschitz-based global optimization algorithms in the literature stemming mainly from ideas due to Piyavskii and Shubert [25, 27]. The Piyavskii-Shubert algorithm is based on the idea of constructing a piecewise linear approximation lying beneath the Lipschitz function. We used DIRECT [16], a sophisticated variant of the Piyavskii-Shubert algorithm. DIRECT attempts to estimate the Lipschitz constant locally, which can possibly speed up convergence.

The main computational cost involved in the numerical optimization of singular values is the retrieval of the r th smallest singular value of $\mathcal{L}(\mu, \Gamma, A, B)$ at various values of μ and Γ . As we only experimented with small pencils, we used direct solvers for this purpose. For medium to large scale pencils, iterative algorithms such as the Lanczos method [12] are more appropriate.

8 Numerical Experiments

Our algorithm is implemented in Fortran, calling routines from LAPACK for singular value computations, the limited memory BFGS routine written by J. Nocedal [20] for inner maximization problems and an implementation of the DIRECT algorithm by Gablonsky [10] for outer Lipschitz-based minimization. A mex interface provides convenient access via MATLAB.

It should be noted that the current implementation is not very reliable, mainly due to the numerical solution of the outer Lipschitz minimization problem. For the moment, the implementation is intended only for small pencils (*e.g.*, $n, m < 100$).

8.1 Nearest Pencils with Multiple Eigenvalues

As a corollary of Theorem 4.8 it follows that for a square pencil $A - \lambda B$ the nearest pencil having $\mathbb{S} = \{\mu\}$ as a multiple eigenvalue is given by

$$\tau_2(\mathbb{S}) = \sup_{\gamma} \left(\left[\begin{array}{cc} A - \mu B & 0 \\ \gamma B & A - \mu B \end{array} \right] \right).$$

Therefore the distance from $A - \lambda B$ to the nearest square pencil with a multiple eigenvalue is characterized by

$$\inf_{\mu \in \mathbb{C}} \sup_{\gamma} \sigma_{2n-1} \left(\begin{bmatrix} A - \mu B & 0 \\ \gamma B & A - \mu B \end{bmatrix} \right).$$

Specifically, we consider the pencil

$$A - \lambda B = \begin{bmatrix} 2 & -1 & -1 \\ -1 & 2 & -1 \\ -1 & -1 & 2 \end{bmatrix} - \lambda \begin{bmatrix} -1 & 2 & 3 \\ 2 & -1 & 2 \\ 4 & 2 & -1 \end{bmatrix}. \quad (22)$$

Solving the above singular value optimization problem results in a distance of 0.59299 to the nearest pencil with a multiple eigenvalue. By (15), a nearest pencil turns out to be

$$\begin{bmatrix} 1.91465 & -0.57896 & -1.21173 \\ -1.32160 & 1.93256 & -0.57897 \\ -0.72082 & -1.32160 & 1.91466 \end{bmatrix} - \lambda \begin{bmatrix} -1 & 2 & 3 \\ 2 & -1 & 2 \\ 4 & 2 & -1 \end{bmatrix},$$

with the double eigenvalue $\lambda_* = -0.85488$.

This result can be verified by plotting the ϵ -pseudospectrum of $A - \lambda B$ (subject to perturbations in A only), which is the set $\Lambda_\epsilon(A, B)$ containing the eigenvalues of all pencils $(A + \Delta A) - \lambda B$ such that $\|\Delta A\|_2 \leq \epsilon$. Equivalently,

$$\Lambda_\epsilon(A, B) = \{\lambda \in \mathbb{C} : \sigma_{\min}(A - \lambda B) \leq \epsilon\}.$$

It is well known that the smallest ϵ such that two components of $\Lambda_\epsilon(A, B)$ coalesce equals the distance to the nearest pencil with multiple eigenvalues. (See [1] for the case $B = I$, but the result easily extends to arbitrary invertible B .) Figure 1 displays pseudospectra of the pencil in (22) for various levels of ϵ . Indeed, two components of the ϵ -pseudospectrum coalesce for $\epsilon = 0.59299$, confirming our result.

8.2 Nearest Rectangular Pencils with at least Two Eigenvalues

As an example for a rectangular pencil, let us consider the 4×3 pencil

$$A - \lambda B = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0.1 & 0 \\ 0 & 2 & 0.3 \\ 0 & 1 & 2 \end{bmatrix} - \lambda \begin{bmatrix} 0 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}.$$

The KCF of this pencil contains a 4×3 singular block and therefore the pencil has no eigenvalues. However, if the entry a_{22} is set to zero, the KCF of the resulting pencil contains a 2×1 singular block and a 2×2 regular block corresponding to finite eigenvalues. Hence, a perturbation with 2-norm 0.1 is sufficient to have two eigenvalues.

According to the corollaries in Section 5 the distance to the nearest 4×3 pencil with at least two eigenvalues has the characterization

$$\tau_2(\mathbb{C}) = \inf_{\mu \in \mathbb{C}^2} \underbrace{\sup_{\gamma} \sigma_{2n-1} \left(\begin{bmatrix} A - \mu_1 B & 0 \\ \gamma B & A - \mu_2 B \end{bmatrix} \right)}_{=:g(\mu)}. \quad (23)$$

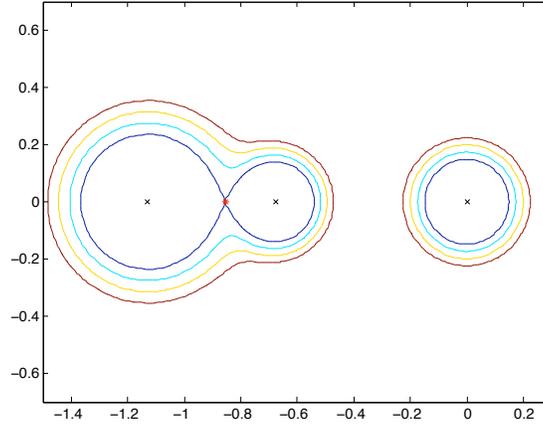


Figure 1: Pseudospectra for the pencil in (22), with eigenvalues marked by the black crosses. Two components of the ϵ -pseudospectrum coalesce for $\epsilon = 0.59299$, corresponding to the distance to a nearest pencil with a multiple eigenvalue at the coalescence point (marked by the asterisk).

Our implementation returns $\tau_2(\mathbb{C}) = 0.03927$. The corresponding nearest pencil (15) is given by

$$\begin{bmatrix} 0.99847 & -0.03697 & -0.01283 \\ 0 & 0.08698 & 0.03689 \\ 0 & 2.00172 & 0.30078 \\ 0.00007 & 1.00095 & 2.00376 \end{bmatrix} - \lambda \begin{bmatrix} 0 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

and has eigenvalues at $\mu_1 = 2.55144$ and $\mu_2 = 1.45405$. This result is confirmed by Figure 2, which illustrates the level sets of the function $g(\mu)$ defined in (23) over \mathbb{R}^2 .

8.3 Nearest Stable Pencils

As a last example, suppose that $Bx'(t) = Ax(t)$ with $A, B \in \mathbb{C}^{n \times n}$ is an unstable descriptor system. The distance to a nearest stable descriptor system is a special case of $\tau_2(\Omega)$, with $\Omega = \mathbb{C}^-$, the left-half of the complex plane. A singular value characterization is given by

$$\tau_2(\mathbb{C}^-) = \inf_{\lambda_j \in \mathbb{C}^-} \sup_{\gamma_{ik} \in \mathbb{C}} \sigma_{n^2-n+1} \left(\begin{bmatrix} A - \lambda_1 B & 0 & & 0 \\ \gamma_{21} B & A - \lambda_2 B & & 0 \\ & & \ddots & \\ \gamma_{n1} B & \gamma_{n2} B & & A - \lambda_n B \end{bmatrix} \right).$$

Specifically, we consider a system with $B = I_2$ and

$$A = \begin{bmatrix} 0.6 - \frac{1}{3}i & -0.2 + \frac{4}{3}i \\ -0.1 + \frac{2}{3}i & 0.5 + \frac{1}{3}i \end{bmatrix}. \quad (24)$$

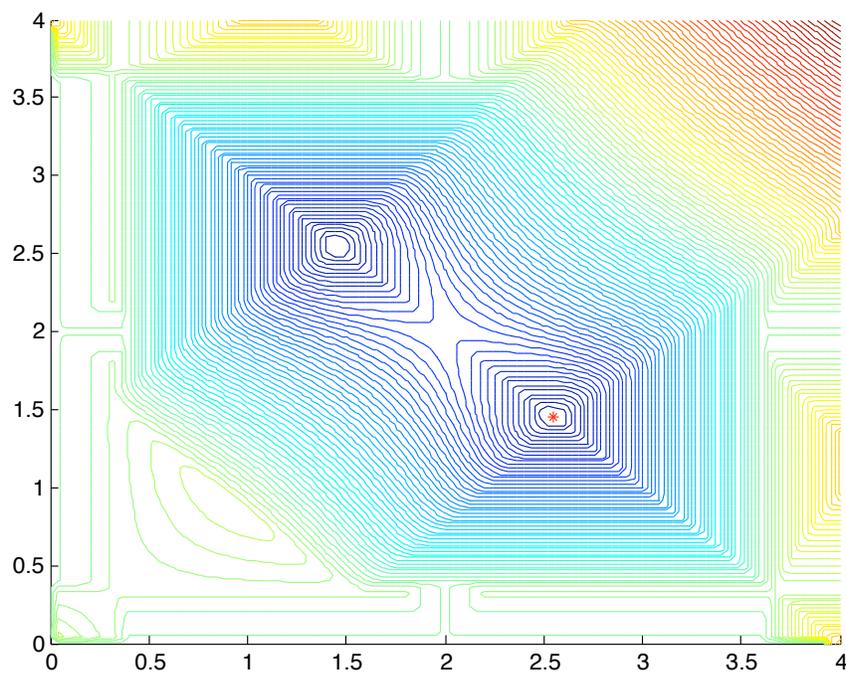


Figure 2: Level sets over \mathbb{R}^2 of the function $g(\mu)$ defined in (23). The asterisk marks the numerically computed global minimizer of g , which corresponds to the eigenvalues of a nearest pencil with two eigenvalues.

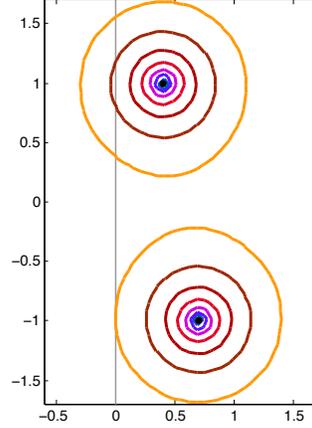


Figure 3: Pseudospectra of the matrix A defined in (24). The orange curve represents the boundary of the ϵ -pseudospectrum for $\epsilon = 0.6610$, the distance to a nearest stable matrix.

Both eigenvalues $\lambda_1 = 0.7 - i$ and $\lambda_2 = 0.4 + i$ are in the right-half plane. Based on the singular value characterization, we have computed the distance to a nearest stable system $x'(t) = (A + \Delta A_*)x(t)$ as 0.6610. The corresponding perturbed matrix

$$A + \Delta A_* = \begin{bmatrix} 0.0681 - 0.3064i & -0.4629 + 1.2524i \\ 0.2047 + 0.5858i & -0.1573 + 0.3064i \end{bmatrix}$$

at a distance of 0.6610 has one eigenvalue $(\lambda_*)_1 = -0.0885 + 0.9547i$ in the left-half plane and the other $(\lambda_*)_2 = -0.9547i$ on the imaginary axis. The ϵ -pseudospectrum of A is depicted in Figure 3. For $\epsilon = 0.6610$, one component of the ϵ -pseudospectrum crosses the imaginary axis, while the other component touches the imaginary axis.

9 Concluding Remarks

In this work a singular value characterization has been derived for the 2-norm of a smallest perturbation to a square or a rectangular pencil $A - \lambda B$ such that the perturbed pencil has a desired set of eigenvalues. The immediate corollaries of this main result are

- (i) a singular value characterization for the 2-norm of the smallest perturbation so that the perturbed pencil has a specified number of its eigenvalues in a desired region in the complex plane, and
- (ii) a singular value characterization for the 2-norm of the smallest perturbation to a rectangular pencil so that it has a specified number of eigenvalues.

Partly motivated by an application explained in the introduction, we allow perturbations to A only. The extension of our results to the case of simultaneously perturbed A and B remains open; additional difficulties can be expected when B is (close to) rank-deficient.

The development of efficient and reliable computational techniques for the solution of the derived singular value optimization problems is still in progress. As of now the optimization problems can be solved numerically only for small pencils with small number of desired eigenvalues. The main task that needs to be addressed from a computational point of view is a reliable and efficient implementation of the DIRECT algorithm for Lipschitz-based optimization. For large pencils it is necessary to develop Lipschitz-based algorithms converging asymptotically faster than the algorithms (such as the DIRECT algorithm) stemming from the Piyavskii-Shubert algorithm. The derivatives from Section 4.1 might constitute a first step in this direction.

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