

Perturbation Bound for the Eigenvalues of a Singular Diagonalizable Matrix

Yimin Wei^{1,2,*} and Yifei Qu²

¹ School of Mathematical Sciences, Fudan University, Shanghai, 200433, China.

² Shanghai Key Laboratory of Contemporary Applied Mathematics, Fudan University, Shanghai, 200433, China.

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Abstract. In this short note, we present a sharp upper bound for the perturbation of eigenvalues of a singular diagonalizable matrix given by Stanley C. Eisenstat [3].

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1. Introduction

For $A \in \mathbb{C}^{n \times n}$, the smallest nonnegative integer k satisfying the rank equation,

$$\text{rank}(A^k) = \text{rank}(A^{k+1})$$

is called the index of the matrix A [1, 9]. If $X \in \mathbb{C}^{n \times n}$ is the unique solution of the three matrix equations

$$A^{k+1}X = A^k, \quad XAX = X, \quad AX = XA,$$

we call X the Drazin inverse A^D . If $\text{index}(A) = 1$, then the Drazin inverse is reduced to the group inverse denoted by $A^\#$ [1, 9].

Let us now recall the classical Bauer-Fike theorem of 1960 and its version from 1999.

Theorem 1.1. (Bauer-Fike Theorem [2, 4]) Let A be diagonalizable — i.e. $A = X\Lambda X^{-1}$, where the diagonal matrix $\Lambda = \text{diag}(\lambda_1, \lambda_2, \dots, \lambda_n)$, λ_i is the eigenvalue of A . Let E be the perturbation of A and μ the eigenvalue of $A + E$. Then

$$\min_i |\lambda_i - \mu| \leq \kappa_2(X) \|E\|_2. \quad (1.1)$$

*Corresponding author. Email addresses: ymwei@fudan.edu.cn, yimin.wei@gmail.com (Y. Wei), 08302010026@fudan.edu.cn (Y. Qu)

If A is invertible, then

$$\min_i \left| \frac{\lambda_i - \mu}{\lambda_i} \right| \leq \kappa_2(X) \|A^{-1}E\|_2, \quad (1.2)$$

where $\kappa_2(X) = \|X^{-1}\|_2 \|X\|_2$ is the condition number of X with respect to the 2-norm.

Wei *et al.* [7, 8] explored how to extend the classical Bauer-Fike theorem to include the singular case, with the help of the group inverse. Later, Eisenstat [3] gave a different version as follows:

Theorem 1.2. Suppose that A is singular diagonalizable —

i.e. $A = X \begin{pmatrix} \Lambda_1 & \\ & \mathbf{0} \end{pmatrix} X^{-1}$, where $\Lambda_1 = \text{diag}(\lambda_1, \lambda_2, \dots, \lambda_r)$, λ_i ($i = 1, 2, \dots, r$) is the nonzero eigenvalue of A . Let E be the perturbation of A , and μ the eigenvalue of $A + E$. If $|\mu| > \kappa_2(X) \|E\|_2$, then

$$\min_i \left| \frac{\lambda_i - \mu}{\lambda_i} \right| \leq \sqrt{1 + \alpha^2} \kappa_2(X) \|A^\# E\|_2, \quad (1.3)$$

where $\alpha = \kappa_2(X) \|E\|_2 / \sqrt{|\mu|^2 - (\kappa_2(X) \|E\|_2)^2}$.

2. Main Results

In this section, we present our main result that improves the upper bound of Ref. [3].

Theorem 2.1. Assume that A is singular diagonalizable and E is the perturbation of A , and μ is the eigenvalue of $A + E$. If $|\mu| > \|X^{-1}(I - AA^\#)EX\|_2$. Then

$$\min_i \left| \frac{\lambda_i - \mu}{\lambda_i} \right| \leq \sqrt{1 + \beta^2} \|X^{-1}A^\#EX\|_2, \quad (2.1)$$

where $\beta = \|X^{-1}(I - AA^\#)EX\|_2 / \sqrt{|\mu|^2 - \|X^{-1}(I - AA^\#)EX\|_2^2}$.

Proof. Let $A = X \begin{pmatrix} \Lambda_1 & \\ & \mathbf{0} \end{pmatrix} X^{-1}$, where $\Lambda_1 = \text{diag}(\lambda_1, \lambda_2, \dots, \lambda_r)$ is a nonsingular diagonal matrix. Let x be an eigenvector of $A + E$ associated with μ , and denote

$$X^{-1}EX = \begin{pmatrix} E_{11} & E_{12} \\ E_{21} & E_{22} \end{pmatrix} \quad \text{and} \quad X^{-1}x = \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}.$$

Since $\mu x = (A + E)x$,

$$\mu \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = \mu X^{-1}x = X^{-1}(A + E)XX^{-1}x = \begin{pmatrix} E_{11} + \Lambda_1 & E_{12} \\ E_{21} & E_{22} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix},$$

so that

$$\mu x_2 = \begin{pmatrix} \mathbf{0} & I \end{pmatrix} \begin{pmatrix} \mathbf{0} & \mathbf{0} \\ E_{21} & E_{22} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}.$$

After a little algebra, we have

$$A^\sharp = X \begin{pmatrix} \Lambda_1^{-1} & \\ & \mathbf{0} \end{pmatrix} X^{-1}, \quad AA^\sharp = X \begin{pmatrix} I & \\ & \mathbf{0} \end{pmatrix} X^{-1}, \quad I - AA^\sharp = X \begin{pmatrix} \mathbf{0} & \\ & I \end{pmatrix} X^{-1}$$

and

$$X^{-1}(I - AA^\sharp)EX = X^{-1}(I - AA^\sharp)XX^{-1}EX = \begin{pmatrix} \mathbf{0} & \mathbf{0} \\ E_{21} & E_{22} \end{pmatrix},$$

so

$$\mu x_2 = \begin{pmatrix} \mathbf{0} & I \end{pmatrix} X^{-1}(I - AA^\sharp)EX \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}.$$

On taking the 2-norm of both sides we have

$$\begin{aligned} |\mu| \|x_2\|_2 &\leq \left\| \begin{pmatrix} E_{21} & E_{22} \end{pmatrix} \right\|_2 \sqrt{\|x_1\|_2^2 + \|x_2\|_2^2} \\ &= \|X^{-1}(I - AA^\sharp)EX\|_2 \sqrt{\|x_1\|_2^2 + \|x_2\|_2^2} \end{aligned}$$

— i.e. $\|x_2\|_2^2 \leq \beta^2 \|x_1\|_2^2$. It is easy to verify that

$$\begin{aligned} \|X^{-1}(I - AA^\sharp)EX\|_2 &= \left\| \begin{pmatrix} \mathbf{0} & \mathbf{0} \\ E_{21} & E_{22} \end{pmatrix} \right\|_2 \leq \left\| \begin{pmatrix} E_{11} & E_{12} \\ E_{21} & E_{22} \end{pmatrix} \right\|_2 \\ &= \|X^{-1}EX\|_2 \leq \kappa_2(X) \|E\|_2. \end{aligned}$$

Since

$$\begin{aligned} \alpha &= \frac{\kappa_2(X) \|E\|_2}{\sqrt{|\mu|^2 - (\kappa_2(X) \|E\|_2)^2}} = \frac{1}{\sqrt{|\mu|^2 / (\kappa_2(X) \|E\|_2)^2 - 1}}, \\ \beta &= \frac{\|X^{-1}(I - AA^\sharp)EX\|_2}{\sqrt{|\mu|^2 - \|X^{-1}(I - AA^\sharp)EX\|_2^2}} = \frac{1}{\sqrt{|\mu|^2 / (\|X^{-1}(I - AA^\sharp)EX\|_2)^2 - 1}}, \end{aligned}$$

it is obvious that $\beta \leq \alpha$. On the other hand, we have

$$\begin{pmatrix} I - \mu \Lambda_1^{-1} & \\ & \mathbf{0} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = X^{-1}A^\sharp(A - \mu I)XX^{-1}x = -X^{-1}A^\sharp Ex$$

and

$$\begin{aligned}
 (I - \mu\Lambda_1^{-1})x &= - \begin{pmatrix} I & \mathbf{0} \end{pmatrix} X^{-1}A^\sharp EX \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} \\
 &= \begin{pmatrix} I & \mathbf{0} \end{pmatrix} \begin{pmatrix} \Lambda^{-1} & \\ & \mathbf{0} \end{pmatrix} \begin{pmatrix} E_{11} & E_{12} \\ E_{21} & E_{22} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} \\
 &= \begin{pmatrix} I & \mathbf{0} \end{pmatrix} \begin{pmatrix} \Lambda_1^{-1}E_{11} & \Lambda_1^{-1}E_{12} \\ \mathbf{0} & \mathbf{0} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}.
 \end{aligned}$$

Taking the 2-norm of both sides and noting that $\|x_2\|_2 \leq \beta\|x_1\|_2$, we therefore obtain

$$\begin{aligned}
 \min_{\lambda_i \neq 0} \left| \frac{\lambda_i - \mu}{\lambda_i} \right| \|x_1\|_2 &\leq \left\| \begin{pmatrix} I & \mathbf{0} \end{pmatrix} \begin{pmatrix} \Lambda_1^{-1}E_{11} & \Lambda_1^{-1}E_{12} \\ \mathbf{0} & \mathbf{0} \end{pmatrix} \right\|_2 \sqrt{\|x_1\|_2^2 + \|x_2\|_2^2} \\
 &= \left\| \begin{pmatrix} \Lambda_1^{-1}E_{11} & \Lambda_1^{-1}E_{12} \\ \mathbf{0} & \mathbf{0} \end{pmatrix} \right\|_2 \sqrt{\|x_1\|_2^2 + \|x_2\|_2^2} \\
 &\leq \sqrt{1 + \beta^2} \left\| \begin{pmatrix} \Lambda_1^{-1}E_{11} & \Lambda_1^{-1}E_{12} \\ \mathbf{0} & \mathbf{0} \end{pmatrix} \right\|_2 \|x_1\|_2 \\
 &\leq \sqrt{1 + \beta^2} \|X^{-1}A^\sharp EX\|_2 \|x_1\|_2,
 \end{aligned}$$

which completes the proof. \square

Remark 2.1. If $|\mu| > \kappa_2(X)\|(I - AA^\sharp)E\|_2$, then we take

$$\beta = \frac{\kappa_2(X)\|(I - AA^\sharp)E\|_2}{\sqrt{|\mu|^2 - (\kappa_2(X)\|(I - AA^\sharp)E\|_2)^2}}$$

so that

$$\min_i \left| \frac{\lambda_i - \mu}{\lambda_i} \right| \leq \sqrt{1 + \beta^2} \kappa_2(X) \|A^\sharp E\|_2.$$

3. Examples

We now discuss two examples illustrating the improvement over the bound in Ref. [3].

Consider the matrix $A \in \mathbb{R}^{3 \times 3}$ given by

$$A = \begin{pmatrix} -0.25 & 0.5 \times 10^{10} & 1.25 \times 10^{10} \\ -0.5 \times 10^{-10} & 1 & 1.5 \\ -1.25 \times 10^{-10} & 1.5 & 1.75 \end{pmatrix}$$

with the three eigenvalues

$$\lambda_1 = 1, \lambda_2 = 2, \lambda_3 = 0 \text{ such that } A = X \text{diag}(1, 2, 0)X^{-1},$$

where

$$X = \begin{pmatrix} 3 & 2 & 1 \\ 2 \times 10^{-10} & 2 \times 10^{-10} & 2 \times 10^{-10} \\ 1 \times 10^{-10} & 2 \times 10^{-10} & -1 \times 10^{-10} \end{pmatrix},$$

$$X^{-1} = \begin{pmatrix} 0.75 & -0.5 \times 10^{10} & -0.25 \times 10^{10} \\ -0.5 & 0.5 \times 10^{10} & 0.5 \times 10^{10} \\ -0.25 & 0.5 \times 10^{10} & -0.25 \times 10^{10} \end{pmatrix}.$$

We choose the perturbation matrix E such that $|E| \leq 10^{-6} \times |A|$, where $|E|$ is the absolute matrix of

$$E = 10^{-16} \times X \begin{pmatrix} 10^5 & -1 \times 10^{10} & 0 \\ 1 & 10^5 & 0 \\ 0 & 0 & 1 \end{pmatrix} X^{-1},$$

We compute

$$X^{-1}AA^\sharp EX = 10^{-16} \times \begin{pmatrix} 10^5 & -1 \times 10^{10} & 0 \\ 1 & 10^5 & 0 \\ 0 & 0 & 0 \end{pmatrix},$$

$$X^{-1}(I - AA^\sharp)EX = 10^{-16} \times \text{diag}(0, 0, 1) \quad \text{and} \quad \Lambda_1^{-1} = \text{diag}(1, 0.5).$$

The matrix $A + E$ has the three eigenvalues

$$\mu_1 = 1 + 0.9976 \times 10^{-11}, \quad \mu_2 = 2 + 1.0006 \times 10^{-11}, \quad \mu_3 = 0.6067 \times 10^{-17}.$$

Let us now compare the two assumptions in Refs. [3, 8], respectively — viz.

$$\kappa_2(X)\|E\|_2 = 7.4246 \times 10^{14} \gg \mu_i, \quad (i = 1, 2)$$

and

$$\|X^{-1}(I - AA^\sharp)EX\|_2 = 1.0000 \times 10^{-16} \ll \mu_i, \quad (i = 1, 2).$$

It is easy to see that our assumption is weaker than that of Ref. [3] so we cannot apply Theorem 1.2, but our bound holds — i.e.

$$\sqrt{1 + \beta^2} \|X^{-1}A^\sharp EX\|_2 = 1.0000 \times 10^{-6}.$$

Let us now consider another matrix $A \in \mathbb{R}^{3 \times 3}$ given by

$$A = \begin{pmatrix} 1.75 & 0.5 \times 10^{-5} & 2.75 \times 10^{-5} \\ -0.5 \times 10^5 & 2 & 3.5 \\ -2.75 \times 10^5 & 3.5 & 4.25 \end{pmatrix}$$

with the three eigenvalues

$$\lambda_1 = 3, \quad \lambda_2 = 5, \quad \lambda_3 = 0 \quad \text{such that} \quad A = X \text{diag}(3, 5, 0) X^{-1},$$

where

$$X = \begin{pmatrix} 3 & 2 & 1 \\ 2 \times 10^5 & 2 \times 10^5 & 2 \times 10^5 \\ 10^5 & 2 \times 10^5 & -1 \times 10^5 \end{pmatrix},$$

$$X^{-1} = \begin{pmatrix} 0.75 & -0.5 \times 10^{-5} & -0.25 \times 10^{-5} \\ -0.5 & 0.5 \times 10^{-5} & 0.5 \times 10^{-5} \\ -0.25 & 0.5 \times 10^{-5} & -0.25 \times 10^{-5} \end{pmatrix}.$$

We select the perturbation matrix E satisfying $|E| \leq 10^{-10} \times |A|$ — viz.

$$E = 10^{-11} \times X \begin{pmatrix} 10^{-5} & -1 \times 10^{-10} & 0 \\ 1 & 10^{-5} & 0 \\ 0 & 0 & 1 \end{pmatrix} X^{-1}.$$

Then

$$X^{-1}AA^{\sharp}EX = \begin{pmatrix} 10^{-16} & -1 \times 10^{-21} & 0 \\ 1 \times 10^{-11} & 10^{-16} & 0 \\ 0 & 0 & 0 \end{pmatrix},$$

and

$$X^{-1}(I - AA^{\sharp})EX = 10^{-11} \times \text{diag}(0, 0, 1), \quad \Lambda_1^{-1} = \text{diag}(0.3333, 0.2000),$$

and $A + E$ has the three eigenvalues

$$\mu_1 = 3 + 6.217248937900877 \times 10^{-15}, \quad \mu_2 = 5 - 7.105427357601002 \times 10^{-15},$$

$$\mu_3 = 1 \times 10^{-11}.$$

Now we can compare with the relative error bounds of Refs. [3, 8], with

$$\kappa_2(X)\|E\|_2 = 0.70544766163927 < \mu_i, \quad (i = 1, 2),$$

and

$$\|X^{-1}(I - AA^{\sharp})EX\|_2 = 1 \times 10^{-11} \ll \mu_i, \quad (i = 1, 2).$$

The bound in Ref. [3] is

$$\sqrt{1 + \alpha^2} \kappa_2(X) \|A^{\sharp}E\|_2 = 0.15277727491342,$$

whereas our new bound is

$$\sqrt{1 + \beta^2} \|X^{-1}A^{\sharp}EX\|_2 = 2.000000000377778 \times 10^{-12}.$$

The relative error bounds for λ_1 and λ_2 are

$$\left| \frac{\lambda_1 - \mu_1}{\lambda_1} \right| = 1.998401444325282 \times 10^{-15},$$

$$\left| \frac{\lambda_2 - \mu_2}{\lambda_2} \right| = 1.443289932012704 \times 10^{-15}.$$

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