# An Improved Bound on the Real Stability Radius* 

L. Qiu<br>The Fields Institute 185 Columbia Street Weat<br>Waterloo, Ontario, Canada N2L 5Z5


#### Abstract

In this paper, we give a new lower bound on the real stability radius of a real atable matrix. We also conjecture that this new lower bound is equal to the exact value of the real stability radius.


## 1 Introduction

One of the long standing open problems in robust control is the computation of the real stability radius of a real stable matrix [3, 6]. The real stability radius of $A \in R^{m \times \pi}$ is defined as

$$
r_{R}(A)=\inf \left\{\mathcal{F}(\Delta A): \Delta A \in R^{m \times=} \text { and } A+\Delta A \text { is unstable }\right\}
$$

## where $\bar{\sigma}(\cdot)$ is the largest singular value.

A closely related concept is the complex stability radius of a complex matrix. The complex stability radius of $A \in C^{\text {ax* }}$ is defined as

$$
\operatorname{rc}(A)=\inf \left\{\bar{\sigma}(\Delta A): \Delta A \in C^{n \times n} \text { and } A+\Delta A \text { is unstable }\right\}
$$

The computation of $\mathrm{rc}(A)$ turns out to be easy. It is now well-known that for stable $A \in \mathrm{C}^{\text {nx }}$

$$
\operatorname{rc}(A)=\inf _{\omega \in \mathbb{W}} \underline{q}\left(A-j \omega I_{n}\right)
$$

where $\Omega(\cdot)$ is the smallest singular value $[4,7,2,5]$. This infimum can be computed by using a bisection algorithm [1].

It is clear that for a real matrix, the complex stability radius gives a lower bound of the real stability radius. In the following, we will always assume that $A$ is a real $n \times n$ stable matrix. Hence,

$$
\begin{equation*}
\operatorname{rr}(A) \geq \operatorname{rc}(A) . \tag{1}
\end{equation*}
$$

Some other lower bounds of the real stability radius are given in [6] as follows

$$
\begin{align*}
& r_{n}(A) \geq \min \left\{\sigma(A), \frac{1}{2} \sigma_{n^{2}-1}\left(A \otimes I_{n}+I_{n} \otimes A\right)\right\}  \tag{2}\\
& r_{n}(A) \geq \frac{1}{2} \sigma\left(A \vee I_{n}+I_{n} \vee A\right)  \tag{3}\\
& r_{n}(A) \geq \min \left\{\sigma(A), \frac{1}{2} \sigma\left(A \wedge I_{n}+I_{n} \wedge A\right)\right\} \tag{4}
\end{align*}
$$

where $\otimes, \vee, \wedge$ denote the Kronecker (tensor) product, symmetrical tensor product and skew-symmetric tensor product respectively [6]. In (2) and in the rest of this paper, we assume that singular values are ordered decreasingly and that $\sigma_{k}(\cdot)$ denotes the $k$-th sigular value.

Inequalities (1)-(4) give easily computable lower bounds to the real stability radius. Moreover, (1)-(4) are actually equalities if $A$ is normal, and (2) and (4) are equalities if $A$ is $2 \times 2$. The tightness of (1)-(4) for a general stable matrix $A$, however, is hard to judge.

In this short paper, we present another lower bound which certainly improves (1) and likely improves (2)-(4). In fact, for all the examples in which we have tested the new lower bound, we have also managed to find destabilizing perturbations whose norms are equal to the respective new lower

[^0]
## E.J. Davison

Department of Electrical Engineering
University of Toronto
Toronto. Ontario, Canada M5S LA4
bounds. This suggests that the new lower bound may turn ont to be equal to the real stability radius. Unfortunately, we can neither prove nor disprove this conjecture at this time.

## 2 Main results

Let $A \in \boldsymbol{R}^{\mathbf{n} \times n}$ be stable. For the convenience of analyais, define

$$
\begin{aligned}
\operatorname{ran}(A)=\inf \{\sigma(\Delta A) & : \Delta A \in R^{n \times n} \text { and } A+\Delta A \text { has } \\
& \text { a pair of imaginary eigenvines }\} .
\end{aligned}
$$

It is clear that

$$
r_{m}(A)=\min \left\{\alpha(A), r_{m}(A)\right\} .
$$

For $\omega \in(0, \infty)$, let $B(\omega)$ be a $2 \times 2$ complex matrix with eigenvalue $j \omega$ and $-j \omega$. Then the rant of

$$
B(\omega) \otimes I_{n}+I_{2} \otimes(A+\Delta A)
$$

is at most $2 n-2$ if $A+\Delta A$ has eigenvalues at $j \omega$ and $-j \omega$. This implies that $\bar{\sigma}(\Delta A)=\bar{\sigma}\left(I_{2} \otimes \Delta A\right)$ is at least $\sigma_{2 m-1}[B(\omega) \otimes$ $\left.I_{n}+I_{2} \otimes A\right]$. Therefore

$$
\begin{equation*}
T_{\omega}(A) \geq \inf _{\omega \in(0, \infty)} \sup _{B(\omega)} \sigma_{2 \pi-1}\left[B(\omega) \otimes I_{\pi}+I_{2} \otimes A\right] . \tag{5}
\end{equation*}
$$

The right hand side of (5) involves a complicated constrained minimax problem. However, it can be simplified as follows. Since $B(\omega)$ has eigenvalues $j \omega$ and $-j \omega$, then there exists a unitary matrix $U$ such that

$$
U^{*} B(\omega) U=\left[\begin{array}{cc}
j \omega & x \\
0 & -j \omega
\end{array}\right]
$$

where $x \in[0, \infty)$. Since $B(\omega) \otimes I_{n}+I_{2} \otimes A$ and $U^{*} B(\omega) U \otimes$ $I_{n}+I_{2} \otimes A$ have the same singular values, it follows that

$$
\begin{aligned}
& \sup _{B(\omega)} \sigma_{2 n-1}\left[B(\omega) \otimes I_{n}+I_{2} \otimes A\right] \\
& \quad=\sup _{x \in[0, \infty)} \sigma_{2 n-1}\left(\left[\begin{array}{cc}
j \omega & x \\
0 & -j \omega
\end{array}\right] \otimes I_{n}+I_{2} \otimes A\right) \\
& \quad=\sup _{x \in(0, \infty)} \sigma_{2 n-1}\left[\begin{array}{cc}
A+j \omega I_{n} & x I_{n} \\
0 & A-j \omega I_{n}
\end{array}\right] .
\end{aligned}
$$

Therefore

$$
r_{\omega \omega}(A) \geq \inf _{\omega \in(0, \infty)} \sup _{x \in\{0, \infty)} \sigma_{2 n-1}\left[\begin{array}{cc}
A+j \omega I_{n} & x I_{n}  \tag{6}\\
0 & A-j \omega I_{n}
\end{array}\right]
$$

The right hand side of (6) is a much easier minimax problem. Now let us denote

$$
\beta(A)=\inf _{\omega \in(0, \infty)} \sup _{x \in(0, \infty)} \sigma_{2 n-1}\left[\begin{array}{cc}
A+j \omega I_{n} & x I_{n} \\
0 & A-j \omega I_{n}
\end{array}\right]
$$

and

$$
\alpha(A)=\min \{\Omega(A), \beta(A)\}
$$

Then we have arrived at our main result.
Theorem $1 \Gamma_{R}(A) \geq \alpha(A)$.

At this moment, we are unable to say much analytically about the new lower bound $\boldsymbol{\alpha}(A)$. However, its computation is a feasible task since it involves a minimax problem with only two real variables. A few simple facts are given in the following.

Fact $1 \alpha(A) \geq r c(A)$.
Fact 1 follows easily from the fact that $\operatorname{rc}(A) \leq \underline{q}(A)$ and

$$
\begin{aligned}
r_{\mathbf{c}}(A) & =\inf _{\omega \in \mathbb{R}} \sigma\left(A-j \omega I_{n}\right) \\
& =\inf _{\omega \in(0, \infty)} \sigma_{2 n-1}\left[\begin{array}{cc}
A+j \omega I_{n} & 0 \\
0 & A-j \omega I_{n}
\end{array}\right] \\
& \leq \inf _{\omega \in(0, \infty)} \sup _{x \in[0, \infty)} \sigma_{2 n-1}\left[\begin{array}{cc}
A+j \omega I_{n} & x I_{n} \\
0 & A-j \omega I_{n}
\end{array}\right]
\end{aligned}
$$

Fact 2 If $A$ is normal or if $A$ is $2 \times 2$, then $\alpha(A)=T_{m}(A)$.
The proof of Fact 2 is tedious but straightforward. It is omitted here.

## 3 Examples

In the numerous examples studied, the lower bound $\alpha(A)$ obtained has always been equal to the real stability radius $\mathrm{rm}(A)$. In these examples, the destabilizing perturbation matrices, whose norms are equal to $\alpha(A)$, are found by a global optimization method. The following three examples are representative:

## Example 1

Let matrix $A$ be

$$
\left[\begin{array}{rrrr}
7.90 \times 10^{1} & 2.00 \times 10^{1} & -3.00 \times 10^{1} & -2.00 \times 10^{1} \\
-4.10 \times 10^{1} & -1.20 \times 10^{1} & 1.70 \times 10^{1} & 1.30 \times 10^{1} \\
1.67 \times 10^{2} & 4.00 \times 10^{1} & -6.00 \times 10^{1} & -3.80 \times 10^{1} \\
3.35 \times 10^{1} & 9.00 \times 10^{0} & -1.45 \times 10^{1} & -1.10 \times 10^{1}
\end{array}\right] .
$$

This matrix is stable with eigenvalues $-1 \pm 10 i$ and $-1 \pm i$. The complex stability radius $r \mathrm{c}(A)=8.234 \times 10^{-2}$.

The solution of the minimax problem is $\beta(A)=1.538 \times$ $10^{-1}$ with $\omega=1.0497$ and $x=1.5549$. Thus

$$
\begin{aligned}
\alpha(A) & =\min \{\ell(A), \theta(A)\} \\
& =\min \left\{2.038 \times 10^{-1}, 1.538 \times 10^{-1}\right\} \\
& =1.538 \times 10^{-1} .
\end{aligned}
$$

## We also find that the following $\Delta A$ matrix

$$
\left[\begin{array}{rrrr}
-4.815 \times 10^{2} & 6.989 \times 10^{2} & 1.091 \times 10^{1} & -6.492 \times 10^{2} \\
8.846 \times 10^{2} & 7.207 \times 10^{2} & 3.627 \times 10^{2} & 7.927 \times 10^{2} \\
-4.382 \times 10^{2} & 2.191 \times 10^{2} & -6.423 \times 10^{2} & -2.426 \times 10^{2} \\
-9.346 \times 10^{2} & 6.663 \times 10^{2} & -2.857 \times 10^{2} & 8.791 \times 10^{2}
\end{array}\right]
$$

is a destabilizing perturbation matrix with $A+\Delta A$ having eigenvalues on the imaginary axis and $\bar{\sigma}(\Delta A)=1.539 \times 10^{-1}$.

## Example 2

Consider the matrix

$$
A=\left[\begin{array}{rrr}
-93.72 & -9520 & -121400 \\
1 & 0 & 0 \\
0 & 1 & 0
\end{array}\right]
$$

This matrix is stable with eigenvalues $-39.609 \pm 82.476 i$ and -14.502 . The complex stability radius $\mathrm{rc}(A)=5.4696 \times 10^{-2}$.

The solution of the minimax problem is $\beta(A)=6.7545 \times$ $10^{-2}$ with $\omega=35.896$ and $x=0$. Thus

$$
\begin{aligned}
\alpha(A) & =\min \{\varrho(A), \beta(A)\} \\
& =\min \left\{9.9694 \times 10^{-1}, 6.7545 \times 10^{-2}\right\} \\
& =6.7545 \times 10^{-2} .
\end{aligned}
$$

We also find that

$$
\Delta A=\left[\begin{array}{rrr}
2.4570 \times 10^{-5} & -3.0951 \times 10^{-4} & 4.8768 \times 10^{-2} \\
-5.7705 \times 10^{-3} & 2.9900 \times 10^{-2} & 1.6763 \times 10^{-2} \\
-6.7337 \times 10^{-2} & -2.4890 \times 10^{-3} & -1.4116 \times 10^{-3}
\end{array}\right]
$$

is a destabilizing perturbation matrix with $A+\Delta A$ having eigenvalues on the imaginary axis and $\bar{\sigma}(\Delta A)=6.7584 \times 10^{-2}$.

## Example 3

Consider the matrix

$$
A=\left[\begin{array}{rrr}
0 & 1 & 100 \\
-10 & -1 & 2 \\
-1 & 1 & -110
\end{array}\right]
$$

This matrix is stable with eigenvalues $-0.90593 \pm 4.3984 i$ and -109.19 . The complex stability radius $\mathrm{rc}(A)=5.0928 \times 10^{-1}$.

The solution of the minimax problem is $\beta(A)=7.6696 \times$ $10^{-1}$ with $\omega=4.4190$ and $x=10$. Thas

$$
\begin{aligned}
\alpha(A) & =\min \{\alpha(A), \beta(A)\} \\
& =\min \left\{1.4703,7.6696 \times 10^{-1}\right\} \\
& =7.6696 \times 10^{-1} .
\end{aligned}
$$

We also find that
$\Delta A=\left[\begin{array}{rrr}5.6912 \times 10^{-1} & -2.6767 \times 10^{-2} & 1.3494 \times 10^{-1} \\ -1.5527 \times 10^{-2} & 7.6475 \times 10^{-1} & 1.6390 \times 10^{-2} \\ 5.1400 \times 10^{-1} & 5.2745 \times 10^{-2} & -1.5247 \times 10^{-1}\end{array}\right]$
is a destabilizing perturbation matrix with $A+\Delta A$ having eigenvalues on the imaginary axis and $\bar{\sigma}(\Delta A)=7.6703 \times 10^{-1}$.

## References

[1] R. Byers. A bisection method for measuring the distance of a stable matrix to the unstable matrices. SIAM J. Sci. Stat. Comput., 9:875-881, 1988.
[2] D. Hinrichsen and A. J. Pritchard. Stability radii of linear systems. Syatems © Control Letters, 7:1-10, 1986.
[3] D. Hinrichsen and A. J. Pritchard. Real and complex stability radii: a survey. In D. Hinrichsen and B. Marartensson, editors, Control of Uncertain Systems. Birkhäuser, Boston, 1990.
[4] W. H. Lee. Robustness analysis for state space models. Technical Report TP-151, Alphatech Inc., 1982.
[5] J. M. Martin. State-space measure for stability robustness. IEEE Trans. Autornat. Contr., AC-32:509-512, 1987.
[6] L. Qiu and E. J. Davison. The stability robustness determination of state space model with real unstructured perturbations. Math. Control Signals Systems, 4:247-267, 1991.
[7] C. Van Loan. How near is a stable matrix to an unstable matrix. Contemporary Math., 47:465-477, 1985.


[^0]:    "This wort has been sepported by the Nataral Sciences and Engineering reaearch Council of Canada under grant no. A4396.

