

An eigenvalue method to calculate dominant poles of a transfer function

Licio Hernanes Bezerra

*Universidade Federal de Santa Catarina, Departamento de Matemática,
Florianópolis, SC, 88040-900, Brazil*

Abstract

Here we give a mathematical proof that a current method that calculates dominant poles is locally convergent. Moreover, the convergence is at least quadratic.

Key words: Eigenvalues, Newton's method, dominant poles, transfer function

MSC: 15A18, 49M15, 65F15, 93B60

1 Introduction

Several methods have been proposed to solve the problem of finding dominant poles of a transfer function. Here we focus in methods arising in Power Systems Control, like those reported in [2], [3], [4].

We pointed out in a discussion enclosed in [4] that one of these methods, called Dominant Pole Method, had local quadratic convergence. This method intended to calculate one dominant pole of a transfer function f given by $f(s) = c^T(A - sI)^{-1}b$, where $A \in \mathbb{R}^{N \times N}$, $b, c \in \mathbb{C}^N$. From a starting value $s^{(0)} \in \mathbb{C}$, this method generates a sequence of complex values from iterations of the following scheme:

$$s^{(k+1)} = \frac{y_k^T A x_k}{y_k^T x_k},$$

where $x_k = (A - s^{(k)}I)^{-1}b$ and $y_k^T = c^T(A - s^{(k)}I)^{-1}$. Simple calculations show that this expression corresponds to the classical Newton method for finding a zero of the function g given by $g(s) = \frac{1}{c^T(A - sI)^{-1}b}$.

Email address: licio@mtm.ufsc.br (Licio Hernanes Bezerra).

A generalization of this method in order to calculate several dominant poles of that transfer function was proposed in [3] and was called the Dominant Pole Eigenvalue Solver (DPSE). There, it was expected that dominant poles would be yielded by iterating the following scheme:

$$\{s_1^{(k+1)}, \dots, s_n^{(k+1)}\} = \lambda((Y_k^T X_k)^{-1} (Y_k^T A X_k))$$

where

$$X_k e_i = \frac{(A - s_i^{(k)} I)^{-1} b}{c^T (A - s_i^{(k)})^{-1} b}$$

and

$$e_i^T Y_k = \frac{c^T (A - s_i^{(k)} I)^{-1}}{c^T (A - s_i^{(k)})^{-1} b}.$$

In this scheme, and from now on, $\lambda(A)$ denotes the spectrum of the matrix A , and $\{e_1, \dots, e_N\}$ is the canonical basis of \mathbb{R}^N .

The purpose of this paper is to present a view of DPSE from a slight different perspective. We will see that the eigenvalues of A are superattracting fixed points of the scheme defined by this method, which leads to quadratic convergence to them.

2 Preliminary results

Let $A \in \mathbb{R}^{N \times N}$ be a matrix with N distinct eigenvalues. Let $b, c \in \mathbb{R}^N$ be two unit vectors such that the transfer function

$$f(s) = c^T (A - sI)^{-1} b$$

has p dominant poles ($1 \leq p \ll N$), that is, for a spectral decomposition of A , $A = PDP^{-1}$,

$$c^T (A - sI)^{-1} b = \sum_{i=1}^N \frac{r_i}{\lambda_i - s}, \quad |r_1| \geq \dots \geq |r_p| >> |r_{p+1}| \geq \dots \geq |r_N| \geq 0,$$

where $r_i = (e_i^T P^{-1} b)(c^T P e_i)$, $\lambda_i = D_{ii}$.

First of all, we will show that, for each k , the matrix $M_k = (Y_k^T X_k)^{-1} (Y_k^T A X_k)$ is well defined, if some conditions were satisfied. The local quadratic convergence of the method will be proved in the next section.

Let $S = (s_1 \cdots s_p)^T \in \mathbb{C}^p$, such that $(\forall i, j)$ $s_i \neq s_j$, if $i \neq j$. Suppose that $(\forall k)$ s_k is not an eigenvalue of A . For $k = 1, \dots, p$ let

$$x_k = \frac{(A - s_k I)^{-1} b}{c^T (A - s_k I)^{-1} b}, \quad y_k^T = \frac{c^T (A - s_k I)^{-1}}{c^T (A - s_k I)^{-1} b}.$$

Remark 1 Note that

$$x_k = \frac{\text{Adj}(A - s_k I) b}{c^T \text{Adj}(A - s_k I) b}, \quad y_k^T = \frac{c^T \text{Adj}(A - s_k I)}{c^T \text{Adj}(A - s_k I) b}.$$

Therefore, the definition of x_k and y_k would make sense even when s_k is a simple eigenvalue of A :

$$x_k = \frac{P e_j}{c^T P e_j}, \quad y_k^T = \frac{e_j^T P^{-1}}{e_j^T P^{-1} b},$$

where $1 \leq j \leq N$ is such that $d_{jj} = s_k$. Moreover, x_k and y_k are entire functions of s .

Lemma 2 Let $A \in \mathbb{R}^{N \times N}$ be a matrix with N distinct eigenvalues. Let $S = (s_1 \cdots s_p)^T \in \mathbb{C}^p$, such that $(\forall i, j)$ $s_i \neq s_j$, if $i \neq j$. Let $X = [x_1 \cdots x_p]$ and $Y = [y_1 \cdots y_p]$, where $(\forall k)$ x_k and y_k are defined as above. Then the matrix $Y^T X$ is symmetric and non-singular.

PROOF. First, suppose that $(\forall k)$ s_k is not an eigenvalue of A . Therefore,

$$\begin{aligned} (Y^T X)_{ij} &= e_i^T Y^T X e_j = \frac{c^T (A - s_i I)^{-1}}{c^T (A - s_i I)^{-1} b} \frac{(A - s_j I)^{-1} b}{c^T (A - s_j I)^{-1} b} = \\ &= \frac{c^T (A - s_i I)^{-1}}{c^T (A - s_i I)^{-1} b} \frac{(A - s_j I)^{-1} b}{c^T (A - s_j I)^{-1} b} = \frac{c^T P (A - s_i I)^{-1}}{c^T (A - s_i I)^{-1} b} \frac{(A - s_j I)^{-1} P^{-1} b}{c^T (A - s_j I)^{-1} b} = \\ &= \frac{(\lambda_1 - s_i, \dots, \lambda_N - s_i) \text{diag}(P^T c)}{c^T (A - s_i I)^{-1} b} \frac{\text{diag}(P^{-1} b) (\lambda_1 - s_j, \dots, \lambda_N - s_j)^T}{c^T (A - s_j I)^{-1} b}. \end{aligned}$$

Let $G \in \mathbb{C}^{N \times p}$ be defined by $G_{ij} = (\lambda_i - s_j)^{-1}$. Let R be the $N \times N$ diagonal matrix such that $R_{ii} = (c^T P e_i)(e_i^T P^{-1} b)$, that is, the residual r_i . Let E be the $N \times N$ diagonal matrix defined by $E_{ii} = [c^T (A - s_i I)^{-1} b]^{-1}$. Then, $Y^T X = E G^T R G E$.

Since $|r_1|, \dots, |r_p|$ are nonzero, the rank of R is at least p . $(\forall i)$ $E_{ii} \neq 0$ for s_i is not an eigenvalue. Moreover, since the submatrix $G(1:p, 1:p)$ is a non-singular Cauchy matrix [1], the rank of $R G G^T$ is p . Therefore, the rank of $Y^T X$ is p .

If for some k s_k is an eigenvalue of A , let $E_{kk} = R_{kk}$ and $Ge_k = e_k$, and the proof works with slight modifications.

□

Remark 3 In practice, the columns vectors x_k, y_k are obtained after normalizing the vectors $(A - s_k I)^{-1}b$ and $(A - s_k I)^{-T}c$, and dividing both the yielding vectors z_k, w_k , respectively, by $c^T z_k$ (which is equal to $b^T w_k$). Notice that the result is the same in exact arithmetic. This procedure has diminished numerical errors near convergence.

3 DPSE has local quadratic convergence

Let $M = (Y^T X)^{-1} Y^T A X$. Note that if s_i is an eigenvalue of A then, by **Remark 1**, $Y^T A X e_i = s_i Y^T X e_i$. Thus s_i is also an eigenvalue of M .

Now, since

$$A X e_i = A \frac{(A - s_i I)^{-1} b}{c^T (A - s_i I)^{-1} b} = s_i X e_i + \frac{b}{c^T (A - s_i I)^{-1} b},$$

it follows that

$$M = \text{diag}(S) + (Y^T X)^{-1} Y^T B,$$

where $\text{diag}(S)$, as above, is the diagonal matrix defined with the elements of the vector S in the diagonal, and $B e_i = b / c^T (A - s_i I)^{-1} b$ (if s_i is an eigenvalue of A , then $A X e_i = s_i X e_i$ and $B e_i = 0$). Hence M is a rank-one perturbation of the diagonal matrix $\text{diag}(S)$.

Definition 4 Suppose X is a topological space and \sim is an equivalence relation on X . We define a topology on the quotient set X / \sim (the set consisting of all equivalence classes of \sim) as follows: a subset $V \subseteq X / \sim$ is open in X / \sim if and only if its preimage $q^{-1}(V)$ is open in X , where $q : X \rightarrow X / \sim$ is the projection map which sends each element of X to its equivalence class. The quotient set X / \sim with this topology is said to be a quotient space.

Now, let $P \mathbb{C}^p$ be the quotient space \mathbb{C}^p / \sim , where $x \sim y$ iff there is a permutation matrix P such that $y = Px$. Let $\Omega = \{(s_1, \dots, s_p) | s_i \neq s_j, \text{ if } i \neq j\} / \sim$. Ω is an open set of $P \mathbb{C}^p$.

Let $\lambda_1, \dots, \lambda_p$ be distinct eigenvalues of A . Since the spectrum of a matrix depends continuously on its entries, let \mathcal{O} be an open set of Ω which contains $(\lambda_1, \dots, \lambda_p) / \sim$ such that the eigenvalues of M are simple.

Let $F : \mathcal{O} \rightarrow P\mathbb{C}^p$ be the function defined as follows: if $M = VTV^{-1}$ is a spectral decomposition of M , $F(S)$ is the class of equivalence of $(F_1(S), \dots, F_p(S))$ where

$$F_i(S) = s_i + \frac{c^T XVe_i}{c^T(A - s_i I)^{-1} XVe_i}$$

Since $c^T(A - s_i I)^{-1}A = c^T + s_i c^T(A - s_i I)^{-1}$, and $c^T(A - s_i I)^{-1}AXVe_i = t_{ii}c^T(A - s_i I)^{-1} XVe_i$, it follows that

$$c^T XVe_i = (t_{ii} - s_i)c^T(A - s_i I)^{-1} XVe_i.$$

Therefore, $F_i(S) = t_{ii}$. Thus, F is well defined. Moreover, since the eigenvalues of M are simple, F is a differentiable function.

It is not difficult to see that (the class of) a p -uple of distinct eigenvalues $(\lambda_1, \dots, \lambda_p)$ is a fixed point of F . For if $A = PDP^{-1}$ and $S = (\lambda_1, \dots, \lambda_p)$, then

$$e_i^T Y X e_j = \frac{e_{k_i}^T P^{-1} P e_{k_j}}{e_{k_i}^T P^{-1} b c^T P e_{k_j}} = \frac{e_{k_i}^T e_{k_j}}{e_{k_i}^T P^{-1} b c^T P e_{k_j}}$$

and

$$e_i^T Y A X e_j = \frac{e_{k_i}^T P^{-1} A P e_{k_j}}{e_{k_i}^T P^{-1} b c^T P e_{k_j}} = \frac{e_{k_i}^T D e_{k_j}}{e_{k_i}^T P^{-1} b c^T P e_{k_j}}$$

where $1 \leq k_r \leq N$ is such that $d_{k_r k_r} = \lambda_r$. Hence $M = \text{diag}(d_{k_1 k_1}, \dots, d_{k_p k_p})$, and so $F(S/\sim) = S/\sim$.

The following theorem is the main goal of this paper.

Theorem 5 *If for each iteration k the s_i are distinct then the DPSE scheme has local quadratic convergence.*

PROOF. *The result follows once it is established that $DF(\Lambda) = 0$, where $\Lambda = (\lambda_1, \dots, \lambda_p)$. To this end, one computes that*

$$\begin{aligned} \frac{\partial F_i}{\partial s_j}(\Lambda) &= \delta_{ij} + \det(A - \lambda_i I) \frac{c^T \frac{\partial}{\partial s_j}(XVe_i)}{c^T \text{Adj}(A - \lambda_i I) XVe_i} \\ &\quad - \delta_{ij} \frac{c^T XVe_i}{(c^T \text{Adj}(A - \lambda_i I) XVe_i)^2} c^T (\text{Adj}(A - \lambda_i I))^2 XVe_i \\ &\quad - \det(A - \lambda_i I) \frac{c^T XVe_i}{(c^T \text{Adj}(A - \lambda_i I) XVe_i)^2} c^T \text{Adj}(A - \lambda_i I) \frac{\partial}{\partial s_j}(XVe_i) = \\ &= \delta_{ij} - \delta_{ij} \frac{c^T XVe_i}{(c^T \text{Adj}(A - \lambda_i I) XVe_i)^2} c^T (\text{Adj}(A - \lambda_i I))^2 XVe_i \\ \text{where } \delta_{ij} &= \begin{cases} 1, & \text{if } i = j; \\ 0 & \text{otherwise.} \end{cases} \end{aligned}$$

For $S = \Lambda$, it follows that V is the identity matrix, and so,

$$\begin{aligned}
& \frac{(c^T X V e_i)(c^T (\text{Adj}(A - \lambda_i I))^2 X V e_i)}{(c^T \text{Adj}(A - \lambda_i I) X V e_i)^2} = \\
& = \frac{(c^T X e_i)(c^T (P e_{k_i} e_{k_i}^T P^{-1})^2 X e_i)}{(c^T P e_{k_i} e_{k_i}^T P^{-1} X e_i)^2} = \frac{(c^T X e_i)(c^T P e_{k_i} e_{k_i}^T P^{-1} X e_i)}{(c^T P e_{k_i} e_{k_i}^T P^{-1} X e_i)^2} = \\
& = \frac{c^T X e_i}{c^T P e_{k_i} e_{k_i}^T P^{-1} X e_i} = \frac{c^T X e_i}{c^T P e_{k_i} e_{k_i}^T P^{-1} P e_{k_i}} = \\
& \quad \frac{c^T X e_i}{c^T P e_{k_i}} = 1
\end{aligned}$$

Therefore, $\frac{\partial F_i}{\partial s_j}(\Lambda) = 0$. \square

4 Conclusions

DPSE has been extensively applied and become popular in model reductions of large linear systems (see [3], [4]). In this paper it was proven that DPSE is like a Newton's method: its convergence is quadratic once one of its iterates is attracted by a fixed point. However, there is no proof whatsoever that DPSE converges to dominant poles in the sense of [3]. This will depend on the basins of attraction of the fixed points and on the initial point selection. Moreover, in practice it has been seen that the performance of DPSE as an eigensolver depends enormously of the vectors b and c , besides the initial vector for its scheme. Some experiments with DPSE as a general eigensolver are reported in [2].

References

- [1] R. Bellman, *Introduction to Matrix Analysis*, 2nd ed. (SIAM, Philadelphia, 1997).
- [2] Licio H. Bezerra, Carlos Tomei and R. Alan McCoy, Möbius Transforms and Solvers for Large Sparse Generalized Nonsymmetric Eigenvalue Problems, Tech. Rep. TR/PA/98/03, CERFACS, Toulouse (1998).
- [3] N. Martins, The Dominant Pole Spectrum Eigensolver, *IEEE Trans. on Power Systems* **12**(1) (1997), 245-254.
- [4] N. Martins, L. T. G. Lima and H. J. C. P. Pinto, Computing Dominant Poles of Very High Order Transfer Functions, *IEEE Trans. on Power Systems* **11**(1) (1996), 162-170.