

## A NOTE ON COMPUTING THE GENERALIZED INVERSE $A_{T,S}^{(2)}$ OF A MATRIX $A$

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The generalized inverse  $A_{T,S}^{(2)}$  of a matrix  $A$  is a  $\{2\}$ -inverse of  $A$  with the prescribed range  $T$  and null space  $S$ . A representation for the generalized inverse  $A_{T,S}^{(2)}$  has been recently developed with the condition  $\sigma(GA|_T) \subset (0, \infty)$ , where  $G$  is a matrix with  $R(G) = T$  and  $N(G) = S$ . In this note, we remove the above condition. Three types of iterative methods for  $A_{T,S}^{(2)}$  are presented if  $\sigma(GA|_T)$  is a subset of the open right half-plane and they are extensions of existing computational procedures of  $A_{T,S}^{(2)}$ , including special cases such as the weighted Moore-Penrose inverse  $A_{M,N}^\dagger$  and the Drazin inverse  $A^D$ . Numerical examples are given to illustrate our results.

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**1. Introduction.** Given a complex matrix  $A \in \mathbb{C}^{m \times n}$ , any matrix  $X \in \mathbb{C}^{n \times m}$  satisfying  $XAX = X$  is called a  $\{2\}$ -inverse of  $A$ . Let  $T$  and  $S$  be subspaces of  $\mathbb{C}^n$  and  $\mathbb{C}^m$ , respectively. A matrix  $X \in \mathbb{C}^{n \times m}$  is called a  $\{2\}$ -inverse of  $A$  with the prescribed range  $T$  and null space  $S$ , denoted by  $A_{T,S}^{(2)}$ , if the following conditions are satisfied:

$$XAX = X, \quad R(X) = T, \quad N(X) = S, \quad (1.1)$$

where  $R(X)$  is the range of  $X$  and  $N(X)$  is the null space of  $X$ . It is a well-known fact [1] that if  $\dim T = \dim S^\perp \leq \text{rank}(A)$ , then there exists a unique  $A_{T,S}^{(2)}$  if and only if  $AT \oplus S = \mathbb{C}^m$ . It is obvious from the definition above that  $AA_{T,S}^{(2)} = P_{AT,S}$  and  $A_{T,S}^{(2)}A = P_{T,(A^*S^\perp)^\perp}$ , where  $P_{S_1,S_2}$  is the projector on the subspace  $S_1$  along the subspace  $S_2$ .

There are seven types of important  $\{2\}$ -inverses of  $A$ : the Moore-Penrose inverse  $A^\dagger$ , the weighted Moore-Penrose inverse  $A_{M,N}^\dagger$ , the  $W$ -weighed Drazin inverse  $A_{d,w}$ , the Drazin inverse  $A^D$ , the group inverse  $A^\#$ , the Bott-Duffin inverse  $A_{(L)}^{(-1)}$ , and the generalized Bott-Duffin inverse  $A_{(L)}^{(\dagger)}$ . All of them are the special cases of the generalized inverse  $A_{T,S}^{(2)}$  of  $A$  for specific  $T$  and  $S$ .

**LEMMA 1.1.** (a) Let  $A \in \mathbb{C}^{m \times n}$  [1]. Then, for the Moore-Penrose inverse  $A^\dagger$  and the weighted Moore-Penrose inverse  $A_{M,N}^\dagger$ ,

- (i)  $A^\dagger = A_{R(A^*),N(A^*)}^{(2)}$ ;
- (ii)  $A_{M,N}^\dagger = A_{R(N^{-1}A^*M),N(N^{-1}A^*M)}^{(2)}$ , where  $N$  and  $M$  are Hermitian positive definite matrices of order  $n$  and  $m$ , respectively;
- (iii)  $A_{d,w} = (WAW)_{R(A(WA)^q),N(A(WA)^q)}^{(2)}$ , where  $W \in \mathbb{C}^{n \times m}$  and  $q = \text{Ind}(WA)$ , the index of  $WA$ .

- (b) [1, 2, 3] Let  $A \in \mathbb{C}^{n \times n}$ . Then, for the Drazin inverse  $A^D$ , the group inverse  $A^\#$ , the Bott-Duffin inverse  $A_{(L)}^{(-1)}$ , and the generalized Bott-Duffin inverse  $A_{(L)}^{(+)}$ ,
  - (iv)  $A^D = A_{R(A^k), N(A^k)}^{(2)}$ , where  $k = \text{Ind}(A)$ ;
  - (v) in particular, when  $\text{Ind}(A) = 1$ ,  $A^\# = A_{R(A), N(A)}^{(2)}$ ;
  - (vi)  $A_{(L)}^{(-1)} = P_L(AP_L + P_{L^\perp})^{-1} = A_{L, L^\perp}^{(2)}$ , where  $L$  is a subspace of  $\mathbb{C}^n$  such that  $AL \oplus L^\perp = \mathbb{C}^n$  and  $P_L$  is the orthogonal projector on  $L$ ;
  - (vii)  $A_{(L)}^{(+)} = A_{(S)}^{(-1)} = A_{S, S^\perp}^{(2)}$ , where  $S = R(P_L A)$ .

The  $\{2\}$ -inverse has many applications, for example, the application in the iterative methods for solving nonlinear equations [1, 9] and the applications to statistics [6, 7]. In particular,  $\{2\}$ -inverse plays an important role in stable approximations of ill-posed problems and in linear and nonlinear problems involving rank-deficient generalized inverse [8, 12]. In literature, researchers have proposed many numerical methods for computing  $A_{T,S}^{(2)}$ , see [2, 3, 11, 13, 15, 16, 18].

As usual, we denote the spectrum and the spectral radius of  $A$  by  $\sigma(A)$  and  $\rho(A)$ , respectively. The notation  $\|\cdot\|$  stands for the spectral norm. The following theorem applied in this note is from the theory of semi-iterative method.

**THEOREM 1.2** (see [5]). *Let  $B \in \mathbb{C}^{n \times n}$  be a nonsingular matrix and let  $\sigma(B) \subset \Omega$ , where  $\Omega$  is a simply connected compact set excluding origin. If a sequence of polynomials  $\{s_m(z)\}_{m=0}^\infty$  uniformly converges to  $1/z$  on  $\Omega$ , then  $\{s_m(B)\}$  converges to  $B^{-1}$ .*

In this note, a representation for the generalized inverse  $A_{T,S}^{(2)}$  with a condition  $\sigma(GA|_T) \subset \{z : \text{Re}(z) > 0\}$ , where  $G$  is a matrix with  $R(G) = T$  and  $N(G) = S$  is presented in Section 2. Euler-Knopp iterative method and semi-iterative methods for  $A_{T,S}^{(2)}$  with linear convergence are derived in Section 3. Quadratically convergent methods for  $A_{T,S}^{(2)}$  are developed in Section 4. Finally, numerical examples are given to illustrate our results.

**2. Representation.** In this section, we give a representation for the generalized inverse  $A_{T,S}^{(2)}$ , which may be viewed as an application of the classical theory summability to the representation of generalized inverse.

**LEMMA 2.1** (see [13]). *Suppose  $A \in \mathbb{C}^{m \times n}$ . Let  $T$  and  $S$  be subspaces of  $\mathbb{C}^n$  and  $\mathbb{C}^m$ , respectively, such that  $AT \oplus S = \mathbb{C}^m$ . Suppose that  $G \in \mathbb{C}^{n \times m}$  satisfies  $R(G) = T$  and  $N(G) = S$ . Denote by  $\tilde{A} = (GA)|_T$  the restriction of  $GA$  on  $T$ . Then  $\text{Ind}(GA) = 1$  and*

$$A_{T,S}^{(2)} = \tilde{A}^{-1}G. \tag{2.1}$$

It follows from Lemma 1.1 that the existence of  $G$  is assured for each of the common seven types of generalized inverses:  $A^*$ ,  $N^{-1}A^*M$ ,  $A(WA)^q$ ,  $A^k$ ,  $A$ ,  $P_L$ , and  $P_S$ . Now we are in a position to establish a presentation theorem.

**THEOREM 2.2.** *Let  $A, T, S, G$ , and  $\tilde{A}$  be as in Lemma 2.1. If  $\sigma(\tilde{A})$  is contained in a simply connected compact set  $\Omega$  excluding origin and a polynomial sequence  $\{s_m(z)\}$  uniformly converges to  $1/z$  on  $\Omega$ , then*

$$A_{T,S}^{(2)} = \lim_{m \rightarrow \infty} s_m(\tilde{A})G. \tag{2.2}$$

Furthermore,

$$\frac{\|s_m(\tilde{A})G - A_{T,S}^{(2)}\|_P}{\|A_{T,S}^{(2)}\|_P} \leq \max_{z \in \sigma(\tilde{A})} |zs_m(z) - 1| + O(\epsilon), \tag{2.3}$$

where  $P$  is invertible such that  $P^{-1}GAP$  is the  $\epsilon$ -Jordan canonical form of  $GA$  and  $\|B\|_P = \|P^{-1}B\|$  for each  $B \in \mathbb{C}^{n \times m}$ .

**PROOF.** Assume that  $\sigma(\tilde{A}) \subset \Omega$ . With applying [Theorem 1.2](#), we get

$$\lim_{m \rightarrow \infty} s_m(\tilde{A}) = \tilde{A}^{-1} \tag{2.4}$$

uniformly on  $\Omega$ . It follows from [Lemma 2.1](#) that

$$\lim_{m \rightarrow \infty} s_m(\tilde{A})G = \tilde{A}^{-1}G = A_{T,S}^{(2)}. \tag{2.5}$$

The error can be written as

$$s_m(\tilde{A})G - A_{T,S}^{(2)} = (s_m(\tilde{A})\tilde{A} - I)A_{T,S}^{(2)}. \tag{2.6}$$

Since  $P$  is nonsingular such that  $P^{-1}GAP$  is the  $\epsilon$ -Jordan canonical form of  $GA$ , it is well known that

$$\|P^{-1}GAP\| \leq \rho(GA) + \epsilon. \tag{2.7}$$

Thus

$$\begin{aligned} \|s_m(\tilde{A})G - A_{T,S}^{(2)}\|_P &= \|P^{-1}(s_m(\tilde{A})\tilde{A} - I)PP^{-1}A_{T,S}^{(2)}\| \\ &\leq \|P^{-1}(s_m(\tilde{A})\tilde{A} - I)P\| \|A_{T,S}^{(2)}\|_P \\ &\leq \left[ \max_{z \in \sigma(\tilde{A})} |s_m(z)z - 1| + O(\epsilon) \right] \|A_{T,S}^{(2)}\|_P. \end{aligned} \tag{2.8}$$

The last inequality is based on the spectrum mapping since  $s_m(z)$  is a polynomial in  $z$ . This completes the proof.  $\square$

In order to make use of this general error estimate in [Theorem 2.2](#) on specific approximation procedures, it will be convenient to have lower and upper bounds for  $\sigma(\tilde{A})$ . This is given in the next lemma.

**LEMMA 2.3.** *Let  $A, T, S, G$ , and  $\tilde{A}$  be as in [Lemma 2.1](#). Then for each  $\lambda \in \sigma(\tilde{A})$ ,*

$$\frac{1}{\|(GA)^\# \|} \leq |\lambda| \leq \|GA\|. \tag{2.9}$$

**PROOF.** We only show the first inequality since the second is trivial. It follows from [Lemma 2.1](#) that  $\text{Ind}(GA) = 1$ . Then the Jordan canonical form of  $GA$  is

$$GA = P \begin{bmatrix} C & 0 \\ 0 & 0 \end{bmatrix} P^{-1}, \quad (GA)^\# = P \begin{bmatrix} C^{-1} & 0 \\ 0 & 0 \end{bmatrix} P^{-1}, \tag{2.10}$$

where  $C$  is invertible. For each  $\lambda \in \sigma(\tilde{A})$ ,  $1/\lambda \in \sigma(\tilde{A}^{-1})$  since  $\tilde{A}$  is invertible. Consequently, we have

$$\frac{1}{|\lambda|} \leq \rho(\tilde{A}^{-1}) = \rho(C^{-1}) \leq \|(GA)^\#\|, \tag{2.11}$$

which leads to (2.9). This completes the proof. □

**REMARK 2.4.** Theorem 2.2 extends the representation of  $A_{T,S}^{(2)}$  in [15] in which  $\sigma(GA|_T) \subset (0, \infty)$  is required. The theorem also recovers the representations of  $A^D$  in [16] and  $A_{M,N}^\dagger$  in [17] as special cases.

**3. Iterative methods for  $A_{T,S}^{(2)}$ .** In this section, we present applications of Theorem 2.2 and Lemma 2.3 in developing specific computational procedures for the generalized inverse  $A_{T,S}^{(2)}$  and estimating corresponding error bounds.

A well-known summability method is called the Euler-Knopp method. A series  $\sum_{m=0}^\infty a_m$  is said to be Euler-Knopp summable with parameter  $\alpha > 0$  to the value  $a$  if the sequence defined by

$$s_m = \alpha \sum_{i=0}^m \sum_{j=0}^i \binom{i}{j} (1-\alpha)^{i-j} \alpha^j a_j \tag{3.1}$$

converges to  $a$ . If we choose  $a_m = (1-z)^m$ ,  $m \geq 0$ , then as the Euler-Knopp transform of the series  $\sum_{m=0}^\infty (1-z)^m$ , we obtain a sequence  $\{s_m(z)\}$ , where

$$s_m(z) = \alpha \sum_{j=0}^m (1-\alpha z)^j. \tag{3.2}$$

Clearly,  $\lim_{m \rightarrow \infty} s_m(z) = 1/z$  uniformly on any compact subset of an open set  $E_\alpha := \{z : |1-\alpha z| < 1\}$ . We assume that  $\sigma(\tilde{A}) \subset \{z : \text{Re}(z) > 0\}$ . Denote

$$\phi := \max_{\lambda \in \sigma(\tilde{A})} \left\{ |\text{Arg } \lambda| : -\frac{\pi}{2} < \text{Arg } \lambda < \frac{\pi}{2} \right\}. \tag{3.3}$$

It follows from Lemma 2.3 that

$$\sigma(\tilde{A}) \subset \{z = r e^{i\theta} : r_1 \leq r \leq r_2, -\phi \leq \theta \leq \phi\} =: F, \tag{3.4}$$

where  $r_1 = 1/\|(GA)^\#\|$  and  $r_2 = \|GA\|$ . It can be shown with the law of Sines that

$$F \subset \{w : |w - g| \leq g\}, \quad \text{for } g = \frac{\|GA\|}{2 \cos \phi}. \tag{3.5}$$

If a parameter  $\alpha$  satisfies

$$0 < \alpha < \frac{2 \cos \phi}{\|GA\|}, \tag{3.6}$$

then  $\sigma(\tilde{A}) \subset E_\alpha$ . There is always a simply connected compact set  $\Omega$  such that  $\sigma(\tilde{A}) \subset \Omega \subset E_\alpha$ . Hence  $s_m(z)$  of (3.2) uniformly converges to  $1/z$  on  $\Omega$ . It follows from Theorem 2.2 that

$$A_{T,S}^{(2)} = \alpha \sum_{n=0}^{\infty} (I - \alpha GA)^n G. \tag{3.7}$$

Notice that if  $A_m$  is the  $m$ th partial sum, that is,  $A_m = \alpha \sum_{j=0}^m (I - \alpha GA)^j G$ , then an iteration form for  $\{A_m\}$  is given by

$$A_0 = \alpha G, \quad A_{m+1} = (I - \alpha GA)A_m + \alpha G, \quad m \geq 0. \tag{3.8}$$

For an error bound, we note that the sequence of polynomials  $\{s_m(z)\}$  satisfies

$$zs_{m+1}(z) - 1 = (1 - \alpha z)(zs_m(z) - 1). \tag{3.9}$$

Thus

$$|zs_m(z) - 1| = |1 - \alpha z|^{m+1} \leq \beta^{m+1} \rightarrow 0, \quad (m \rightarrow \infty), \tag{3.10}$$

where

$$\beta = \max_{z \in \sigma(\tilde{A})} |1 - \alpha z| \leq \max_{z \in F} |1 - \alpha z| < 1. \tag{3.11}$$

Actually, by the maximum modular theorem,  $\max_{z \in F} |1 - \alpha z| = \max_{z \in \partial F} |1 - \alpha z|$ . We denote four parts of  $\partial F$  as follows:

$$\begin{aligned} \Gamma_1 &= \{r_1 e^{i\theta} : -\phi \leq \theta \leq \phi\}, & \Gamma_2 &= \{r e^{i\phi} : r_1 \leq r \leq r_2\}, \\ \Gamma_3 &= \{r_2 e^{i\theta} : -\phi \leq \theta \leq \phi\}, & \Gamma_4 &= \{r e^{-i\phi} : r_1 \leq r \leq r_2\}. \end{aligned} \tag{3.12}$$

If  $z \in \Gamma_1$ , then  $|1 - \alpha z|^2 = 1 - 2\alpha r_1 \cos \theta + \alpha^2 r_1^2$  and it is obvious that

$$\max_{z \in \Gamma_1} |1 - \alpha z| = |1 - \alpha r_1 e^{i\phi}|. \tag{3.13}$$

With an analogous argument, we have

$$\max_{z \in \Gamma_3} |1 - \alpha z| = |1 - \alpha r_2 e^{i\phi}|. \tag{3.14}$$

If  $z \in \Gamma_2 \cup \Gamma_4$ , then  $|1 - \alpha z|^2 = 1 - 2\alpha r \cos \phi + \alpha^2 r^2$  is a quadratic function of  $r$  on  $[r_1, r_2]$ , which achieves its maximum at either  $r = r_1$  or  $r = r_2$ . So

$$\max_{z \in \Gamma_2 \cup \Gamma_4} |1 - \alpha z| = \max \{ |1 - \alpha r_1 e^{i\phi}|, |1 - \alpha r_2 e^{i\phi}| \}. \tag{3.15}$$

It follows from Theorem 2.2 that an error bound is given by

$$\frac{\|A_m - A_{T,S}^{(2)}\|_P}{\|A_{T,S}^{(2)}\|_P} \leq \beta^{m+1} + O(\varepsilon), \tag{3.16}$$

where

$$\beta \leq \max \{ |1 - \alpha e^{i\phi}| / \|(GA)^\#\|, |1 - \alpha e^{i\phi}| \|GA\| \}. \tag{3.17}$$

Therefore, we have shown the following general convergence theorem.

**THEOREM 3.1.** *Let  $A, T, S,$  and  $G$  be as in [Lemma 2.1](#). Suppose the spectrum of  $GA|_T$  is contained in the open right half-plane. Then the sequence  $\{A_m\}$  of [\(3.8\)](#) linearly converges to  $A_{T,S}^{(2)}$ , if  $0 < \alpha < 2 \cos \phi / \|GA\|$ , where  $\phi$  is given by [\(3.3\)](#). Moreover, the relative error is bounded by [\(3.16\)](#).*

We remark that [Theorem 3.1](#) is an extension of corresponding results in [[15, 16](#)].

The procedure of semi-iterative methods [[5, 10](#)] for solving a linear system can easily be extended to solve

$$X = HX + C, \quad \text{for } C \in \mathbb{C}^{n \times n}. \tag{3.18}$$

If  $\rho(H) < 1$ , then a sequence of matrices  $\{X_m\}$ , yielded by

$$X_0 = C; \quad X_{m+1} = HX_m + C \quad (m \geq 0), \tag{3.19}$$

converges to  $(I - H)^{-1}C$ . In general, let  $1 \notin \sigma(H)$ . As usual, based on a sequence of polynomials  $\{p_m(z)\}$  given by

$$p_m(z) = \sum_{i=0}^m \pi_{m,i} z^i, \quad \text{where } \sum_{i=0}^m \pi_{m,i} = 1, \tag{3.20}$$

the corresponding semi-iterative method induced by  $\{p_m(z)\}$  for the computation of  $(I - H)^{-1}C$  is defined as

$$Y_m = \sum_{i=0}^m \pi_{m,i} X_i, \quad m \geq 0. \tag{3.21}$$

Moreover, the matrices  $Y_m$  and the corresponding residual matrices  $R_m$  are given by

$$Y_m = p_m(H)Y_0 + q_{m-1}(H)C, \quad R_m = p_m(H)(C - (I - H)Y_0), \tag{3.22}$$

where

$$q_{m-1}(z) = (1 - p_m(z)) / (1 - z) \quad \text{with } q_{-1}(z) = 0. \tag{3.23}$$

If  $\{q_m(H)\}$  converges to  $(I - H)^{-1}$ , or equivalently, if  $\{p_m(H)\}$  converges to 0, then the sequence  $\{Y_m\}$  of [\(3.21\)](#) converges to  $(I - H)^{-1}C$ . Especially, for  $H = I - GA|_T$  and  $C = G$ ,  $\{Y_m\}$  converges to  $A_{T,S}^{(2)}$ . With an application of [Theorem 1.2](#), we have the following corollary.

**COROLLARY 3.2.** *Let  $A, T, S,$  and  $G$  be as in [Lemma 2.1](#) and let  $H = I - GA|_T$ . If  $\sigma(H)$  is contained in  $\Omega_1$ , a simply connected compact set excluding 1, and  $\{q_m(z)\}$  of [\(3.23\)](#) uniformly converges to  $1/(1 - z)$  on  $\Omega_1$ , then the sequence  $\{Y_m\}$  of [\(3.21\)](#) converges to  $A_{T,S}^{(2)}$  for  $Y_0 = G$ .*

Especially,  $\Omega_1$  is either a complex segment  $[\alpha, \beta]$  excluding 1 or a closed ellipse in the left half-plane  $\{z : \text{Re}(z) < 1\}$  with foci  $\alpha$  and  $\beta$ . Let a sequence of polynomials  $\{p_m(z)\}$  given by

$$p_m(z) = \frac{T_m((z - \delta)/\xi)}{T_m((1 - \delta)/\xi)}, \quad \left( \delta = \frac{\alpha + \beta}{2}, \xi = \frac{\beta - \alpha}{2} \right), \tag{3.24}$$

where  $T_m$  is the  $m$ th Chebyshev polynomial. The semi-iterative method induced by  $\{p_m(z)\}$  is the Chebyshev iterative method optimal for ellipse  $\Omega_1$ . The corresponding two-step stationary method with the same asymptotically optimal convergence rate is given by

$$\begin{aligned} Y_0 &= G; & Y_1 &= \mu(HY_0 + G); \\ Y_{m+1} &= \mu_0(HY_m + G) + \mu_1 Y_m + \mu_2 Y_{m-1}, \quad (m \geq 1), \end{aligned} \tag{3.25}$$

where

$$\mu_0 = \frac{4}{(\sqrt{1 - \beta} + \sqrt{1 - \alpha})^2}, \quad \mu_1 = \frac{\alpha + \beta}{2} \mu_0, \quad \mu_2 = 1 - \mu_0 - \mu_1. \tag{3.26}$$

The sequence  $\{Y_m\}$  converges asymptotically optimally to  $A_{T,S}^{(2)}$ .

**4. Quadratically convergent methods.** Newton-Raphson method for finding the root  $1/z$  of the function  $s(w) = w^{-1} - z$  is given by

$$w_{m+1} = w_m(2 - zw_m), \quad \text{for a suitable } w_0. \tag{4.1}$$

For  $\alpha > 0$ , a sequence of functions  $\{s_m(z)\}$  is defined by

$$s_0(z) = \alpha, \quad s_{m+1}(z) = s_m(z)[2 - zs_m(z)]. \tag{4.2}$$

Let  $z \in \sigma(GA|_T)$  and  $0 < \alpha < 2 \cos \phi / \|GA\|$ . It follows from the recursive form  $zs_{m+1}(z) - 1 = -[zs_m(z) - 1]^2$  that

$$|zs_m(z) - 1| = |\alpha z - 1|^{2^m} \leq \beta^{2^m} \rightarrow 0, \quad \text{as } m \rightarrow \infty, \tag{4.3}$$

where an upper bound of  $\beta$  is given by (3.17).

The great attraction of the Newton-Raphson method is the generally quadratic nature of the convergence. Using the above facts in conjunction with Lemma 2.3, we see that a sequence  $\{s_m(\tilde{A})\}$  defined by

$$s_0(\tilde{A}) = \alpha I, \quad s_{m+1}(\tilde{A}) = s_m(\tilde{A})[2I - \tilde{A}s_m(\tilde{A})] \tag{4.4}$$

has the property that  $\lim_{m \rightarrow \infty} s_m(\tilde{A})G = A_{T,S}^{(2)}$ . If we set  $A_m = s_m(\tilde{A})G$ , then

$$A_0 = \alpha G, \quad A_{m+1} = A_m(2I - AA_m). \tag{4.5}$$

Thus we have the following corollary.

**COROLLARY 4.1.** *Let  $A, T, S$ , and  $G$  be as in Lemma 2.1. Suppose that the spectrum of  $\sigma(GA|_T) \subset \{z : \operatorname{Re}(z) > 0\}$ . Then the sequence  $\{A_m\}$  of (4.5) quadratically converges to  $A_{T,S}^{(2)}$ , for  $0 < \alpha < 2 \cos \phi / \|GA\|$ . Furthermore, an error bound is given by*

$$\|A_m - A_{T,S}^{(2)}\|_p \leq (\beta^{2^m} + O(\epsilon)) \|A_{T,S}^{(2)}\|_p, \quad (4.6)$$

where an upper bound of  $\beta$  is given in (3.17).

We remark that Corollary 4.1 is an extension of [4, 13, 15]. It covers iterative methods for  $A_{M,N}^\dagger$  in [17].

The Newton-Raphson procedure can be speeded up by the successive matrix squaring technique in [14] if two parallel processors are available. In fact, the sequence in (4.5) is mathematically equivalent to

$$\begin{aligned} A_0 &= \alpha G, & P_0 &= I - \alpha GA, \\ A_{m+1} &= (I + P_m)A_m, & P_{m+1} &= P_m^2. \end{aligned} \quad (4.7)$$

There are two matrix multiplications each step both in (4.5) and (4.7). However,  $A_{m+1}$  and  $P_{m+1}$  in (4.7) can be calculated simultaneously.

Two algorithms given by (3.8) and (4.5) are also valid in the case when the spectrum of  $\tilde{A}$  is contained in the left half-plane with slight modification.

Moreover, all results in the previous two sections are valid without the restriction on  $\sigma(GA)$  if  $G$  is substituted by another matrix. This is stated as the following corollary.

**COROLLARY 4.2.** *Let  $A, T, S$ , and  $G$  be as in Lemma 2.1. Then Theorem 3.1 and Corollaries 3.2 and 4.1 are valid without any restriction on the spectrum of  $GA|_T$  if  $G$  is substituted by*

$$G_0 = G(GAG)^*G. \quad (4.8)$$

**PROOF.** It suffices to show that

$$R(G_0) = R(G), \quad N(G_0) = N(G), \quad \sigma(G_0A|_T) \subset (0, \infty). \quad (4.9)$$

As a matter of fact (4.9) is a direct result of [4, Lemma 3.4].  $\square$

We remark a disadvantage of the choice  $G_0$  of (4.8). In the case of computing  $A^D$  with  $\operatorname{Ind}(A) = k \geq 3$ ,  $G_0 = A^k(A^{2k+1})^*A^k$ , the condition number of  $G_0A|_T$  will be extremely large since  $\operatorname{cond}(G_0A|_T) = \operatorname{cond}(A|_T)^{4k+2}$ . An accurate numerical solution cannot be obtained if there is any round-off error in  $A$ .

**5. Examples.** Three examples are given in this section to illustrate the computations of three types of  $A_{T,S}^{(2)}$ . All calculations were performed on a PC with MATLAB.

**EXAMPLE 5.1.** Let  $A$  and  $W$  be 20 by 10 and 10 by 10 random matrices with entries on  $[-1, 1]$ , respectively. We choose  $M$  and  $N$  as random symmetric and positive definite matrices of order 20 and 10, respectively. The stop criterion in (4.5) is

$\|A_m - A_{m-1}\|_\infty \leq \epsilon = 10^{-10}$ . Three special cases  $A^\dagger$ ,  $A_{M,N}^\dagger$ , and  $A_{d,w}$  are computed in this example. The choices of  $G$ , the number of iterations required and the norm of errors are listed in Table 5.1.

TABLE 5.1. Newton-Raphson method for  $A^\dagger$ ,  $A_{M,N}^\dagger$ , and  $A_{d,w}$ .

$A_{T,S}^{(2)}$	$G$	$m$	$\ A_m - A_{m-1}\ _\infty$	$\ A_m - A_{T,S}^{(2)}\ _\infty$
$A^\dagger$	$A^*$	11	3.25E-14	2.56E-15
$A_{M,N}^\dagger$	$N^{-1}A^*M$	25	1.03E-15	3.09E-15
$A_{d,w}$	$AWA((WA)^*)^4WA$	36	1.96E-13	1.76E-07

It is remarked that the better accuracy of  $A_{d,w}$  never be achieved and 1.7E-07 is the best error of  $\|A_m - A_{d,w}\|_\infty$  even if  $\|A_m - A_{m-1}\|_\infty \leq \epsilon = 10^{-10}$  is used as a stop criterion. This is because the condition number of  $GAW|_T$  is as large as  $10^{10}$ . If 2-step semi-iterative method of (3.25) is applied to compute  $A_{T,S}^{(2)}$ , then  $\{Y_m\}$  converges to  $A^\dagger$  after 54 iterations. However, the method fails to converge after 1500 iterations in other two cases because the segments  $[\alpha, \beta]$  containing  $\sigma(GA|_T)$  are  $[-187970, 0.796]$  and  $[-355800, 0.9997]$ , respectively, so that the rate of asymptotic convergence is too slow.

**EXAMPLE 5.2.** Let  $A$  be 8 by 8 matrix with a complex spectrum given by

$$A = \begin{bmatrix} \frac{3}{2} & \frac{1}{3} & 0 & 0 & 0 & 0 & 0 & 0 \\ -\frac{1}{4} & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ -1 & -1 & \frac{3}{4} & -\frac{3}{4} & 0 & 0 & 0 & 0 \\ -1 & -1 & -\frac{3}{4} & \frac{3}{4} & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \frac{3}{4} & -\frac{3}{4} & -1 & -1 \\ 0 & 0 & -1 & 0 & -\frac{3}{4} & \frac{3}{4} & -1 & -1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & -\frac{1}{4} \\ 0 & 0 & 0 & 0 & 0 & 0 & \frac{1}{3} & \frac{3}{2} \end{bmatrix}. \tag{5.1}$$

In order to compute  $A^D$ , we choose  $G = A^2$  since  $\text{Ind}(A) = 2$ . The spectrum of  $GA|_T$ ,  $\sigma(GA|_T) = \{1.875 \pm 0.674i, 1.875 \pm 0.674i, 3.375, 3.375\}$ , is located on the right half-plane. The foci  $\alpha = -2.3$  and  $\beta = -0.5$  of an ellipse containing  $\sigma(I - GA|_T)$  is selected. It requires 28 iterations of 2-step method of (3.25) to compute  $A^D$  with the  $\infty$ -norm of the error less than  $10^{-10}$ . As expected, Newton-Raphson algorithm of (4.5) converges much faster. It achieves the same accuracy with only 8 iterations.

TABLE 5.2.  $A_{T,S}^{(2)}$  of a Toeplitz matrix.

$A_{T,S}^{(2)}$	$G$	No. of it. by Newton's	No. of it. by SIM
$A^\dagger$	$A^*$	10	63
$A_{M,N}^\dagger$	$N^{-1}A^*M$	11	75
$A_{d,w}$	$AWA((WA)^*)^4WA$	31	> 1500

**EXAMPLE 5.3.** Let  $r$  and  $c$  be a row vector and column vector, respectively, such that

$$\begin{aligned}
 r_1 &= c_1 = 2.5, \\
 r_j &= \frac{(-1)^j j}{16} + \frac{i(j-1)}{j}, \quad \text{for } j = 2, 3, \dots, 16, \\
 c_k &= \frac{(-1)^k k}{10}, \quad \text{for } k = 2, 3, \dots, 10.
 \end{aligned}
 \tag{5.2}$$

A  $10 \times 16$  complex Toeplitz matrix  $A$  is constructed by  $r$  and  $c$ . The stop criterion is the same as in Example 5.1.  $M$  and  $N$  are chosen positive definite diagonal matrix related to  $A$ , and  $W$  is a random matrix. The numbers of iterations by Newton's method and SIM method for  $A_{T,S}^{(2)}$  are shown in Table 5.2.

The data shows that Newton's method is much faster than that of SIM.

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