Estimates of Convergence Rate of Parallel Multisplitting Iterative Methods with Their Applications

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1 Introduction

Consider large-scale systems of linear algebraic equations

$$Ax = b \tag{1}$$

where $A \in \mathbb{R}^{n \times n}$ and $b \in \mathbb{R}^n$. O'Leary and White [8] proposed a parallel multisplitting iterative method (the PMI-method) for solving (1) in 1985. Through multisplitting of A

$$A = M_l - N_l;$$
 with $\det(M_l) \neq 0;$ $l = 1, 2, \dots, k,$ (2)

they constructed the iterative procedures

$$y_l^m = M_l^{-1} N_l x^m + M_l^{-1} b;$$
 $l = 1, 2, \dots, k$ (3)

for (1). By introducing weighting matrices E_l for $l=1,2,\cdots,k$ with

$$0 \le E_l \le I; \qquad \sum_{l=1}^k E_l = I, \tag{4}$$

where I is the $n \times n$ identity matrix, they combined (3) and obtained the PMI-method:

$$x^{m+1} = \sum_{l=1}^{k} E_l y_l^m; \qquad m = 0, 1, 2, \cdots$$
 (5)

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The triple (M_l, N_l, E_l) $l = 1, 2, \dots, k$ is called a multisplitting of the matrix A and we can rewrite (5) in the equivalent form as:

$$x^{m+1} = Hx^m + Gb (6)$$

where
$$H = \sum_{l=1}^{k} E_l M_l^{-1} N_l; G = \sum_{l=1}^{k} E_l M_l^{-1}$$
.

Many authors have presented different schemes based on different multisplittings of the coefficient matrix A, for example, PMI-GS and PMI-GSGS [7], PMI-SOR [2], PMI-AOR [10], PMI-GSOR and PMI-GAOR [3]. The convergence of these methods were proved under different conditions. However, the methods used to prove the convergence in [2], [3], [7], [10] were inconvenient and varied. The author knows of new previous estimates of the convergence rate of PMI-method. So it is necessary to simplify and unify the proof of the convergence of PMI-method and to estimate the convergence rate of PMI-methods simply and practically.

2 Estimates of the Convergence Rate of PMI-methods

It is well known that the estimate of asymptotic convergence rate R(H) of iterative method is equivalent to the estimate of the spectral radius $\rho(H)$ of the iterative matrix H, because $R(H) = -\log(\rho(H))$. We will denote M_l, N_l, E_l by $(m_{ij}^l), (n_{ij}^l), (e_{ij}^l)$, respectively, and omit the index $l = 1, 2, \dots, k$. We denote $\sum_{l=1}^k, \sum_{j=1}^n, \sum_{\substack{j=1\\j \neq i}}^n, \max_{1 \leq l \leq k}, \max_{1 \leq k \leq$

Theorem 1. Let A be nonsingular and (M_l, N_l, E_l) be a multisplitting of A. If M_l is SDD (strictly diagonally dominant), then

$$\rho(H) \le \|H\|_{\infty} \le \max_{l} \{ \max_{i} \{ \sum_{j} \frac{|n_{ij}^{l}|}{|m_{ii}^{l}| - \sum_{j \ne i} |m_{ij}^{l}|} \} \}.$$
 (7)

Proof. It is well known that $\rho(H) \leq ||H||_{\infty}$, so we need only to prove the right inequality.

Let $n_l=(n_1^l,n_2^l,\cdots,n_n^l)^T$ be an n-vector and $M_l^{-1}n_l=x_l:=(x_1^l,x_2^l,\cdots,x_n^l)^T$. Thus,

$$\sum_{l} E_{l} M_{l}^{-1} n_{l} = \sum_{l} E_{l} x_{l} = \left(\sum_{l} e_{11}^{l} x_{1}^{l}, \sum_{l} e_{22}^{l} x_{2}^{l}, \cdots, \sum_{l} e_{nn}^{l} x_{n}^{l} \right)^{T}.$$

Since $\sum_{l}e_{ii}^{l}=1$ for $i=1,2,\cdots,n,$ we have

$$\Big\| \sum_{l} E_l M_l^{-1} n_l \Big\|_{\infty} = \max_{i} \{ |\sum_{l} e_{ii}^l x_i^l| \} \le \max_{l} \{ \max_{i} \{ |x_i^l| \} \} := |x_{i_0}^{l_0}|.$$

Consider the i_0 -th equation of $M_{l_0}x_{l_0}=n_{l_0}$.

$$|m_{i_0i_0}^{l_0}|\cdot|x_{i_0}^{l_0}| = \left|n_{i_0}^{l_0} - \sum_{j\neq i} m_{i_0j}^{l_0} x_{i_0}^j\right| \leq |n_{i_0}^{l_0}| + |x_{i_0}^{l_0}| \cdot \sum_{j\neq i} |m_{i_0j}^{l_0}|$$

and this implies

$$|x_{i_0}^{l_0}| \leq \frac{|n_{i_0}^{l_0}|}{|m_{i_0i_0}^{l_0}| - \sum\limits_{j \neq i_0} |m_{i_0j}^{l_0}|} \leq \max_{l} \{\max_i \{\frac{|n_i^l|}{|m_{ii}^l| - |\sum\limits_{j \neq i} m_{ij}^l|} \}\}.$$

Hence

$$\left\| \sum_{l} E_{l} M_{l}^{-1} n_{l} \right\|_{\infty} \leq \max_{l} \left\{ \max_{i} \left\{ \frac{|n_{ij}^{l}|}{|m_{ii}^{l}| - |\sum_{j \neq i} m_{ij}^{l}|} \right\} \right\}.$$

 M_l is SDD. Let $D_l = \operatorname{diag}(M_l)$, $C_l = D_l - M_l$, then $\langle M_l \rangle = |D_l| - |C_l|$, $|D_l^{-1}C_l| \leq |D_l|^{-1}|C_l|$ (in fact, the equality holds). We have

$$\rho(D_l^{-1}C_l) \le \rho(|D_l|^{-1}|C_l|) < 1.$$

Hence M_l is invertible and

$$\begin{split} |M_l^{-1}| &= |(D_l - C_l)^{-1}| = |\sum_{j=0}^{\infty} (D_l^{-1} C_l)^j D_l^{-1}| \\ &\leq \sum_{j=0}^{\infty} (|D_l|^{-1} |C_l|)^j |D_l|^{-1} = (|D_l| - |C_l|)^{-1} = \langle M_l \rangle^{-1}. \end{split}$$

Furthermore

$$|M_l^{-1}N_l| \leq \langle M_l \rangle^{-1}|N_l|; \quad |H| \leq \sum_l E_l|M_l^{-1}N_l| \leq \sum_l E_l\langle M_l \rangle^{-1}|N_l| := F.$$

Let $N_l = (N_1^l, N_2^l, \dots, N_n^l)$, where N_i^l is the *i*-th column vector of N_l . Then

$$\begin{split} \rho(H) & \leq \parallel H \parallel_{\infty} \leq \parallel F \parallel_{\infty} = \max_{i} \{ \sum_{l} (\sum_{l} E_{l} \langle M_{l} \rangle^{-1} | N_{l} |)_{ij} \} \\ & = \max_{i} \{ \sum_{j} (\sum_{l} E_{l} \langle M_{l} \rangle^{-1} | N_{1}^{l} |, \sum_{l} E_{l} \langle M_{l} \rangle^{-1} | N_{2}^{l} |, \cdots, \sum_{l} E_{l} \langle M_{l} \rangle^{-1} | N_{n}^{l} |)_{ij} \} \\ & = \max_{i} \{ \sum_{l} (E_{l} \langle M_{l} \rangle^{-1} \sum_{j} | N_{j}^{l} |)_{i} \} = \parallel \sum_{l} E_{l} \langle M_{l} \rangle^{-1} \sum_{j} | N_{j}^{l} | \parallel_{\infty} \\ & \leq \max_{l} \{ \max_{i} \{ \sum_{j} \frac{(|N_{j}^{l}|)_{i}}{|m_{ij}^{l}| - \sum_{j \neq i} |m_{ij}^{l}|} \} \} = \max_{l} \{ \max_{i} \{ \sum_{j} \frac{|n_{ij}^{l}|}{|m_{ij}^{l}| - \sum_{j \neq i} |m_{ij}^{l}|} \} \}. \end{split}$$

This proves the theorem.

Remark. We can see from the above proof that (7) holds for $M_l \in \mathbb{R}^{n \times n}$, $N_l \in \mathbb{R}^{n \times m}$ under the assumption that M_l is SDD. We can make the same remark on the following theorem and corollaries 1 and 2.

Theorem 2. Under the assumptions of theorem 1 and assumming that M_l is a L-matrix, $N_l \geq 0$, it follows

$$\min_{i} \{ \sum_{l} \sum_{l} E_{l} M_{l}^{-1} N_{l} \} \ge \min_{l} \{ \min_{i} \{ \sum_{j} \frac{|n_{ij}^{l}|}{|m_{ii}^{l}| - \sum_{i \neq i} |m_{ij}^{l}|} \} \}.$$
 (8)

The proof of this theorem is analogous to that of theorem 1.

Corollary 1. Under the assumptions of theorem 2, we have

$$\min_{l} \{ \min_{i} \{ \sum_{j} \frac{n_{ij}^{l}}{\sum_{j} m_{ij}^{l}} \} \} \le \min_{i} \{ \sum_{j} (\sum_{l} E_{l} M_{l}^{-1} N_{l})_{ij} \} \le \rho(H) \le \|H\|_{\infty}$$

$$= \max_{i} \{ \sum_{j} (\sum_{l} E_{l} M_{l}^{-1} N_{l})_{ij} \} \le \max_{l} \{ \max_{i} \{ \sum_{j} \frac{n_{ij}^{l}}{\sum_{j} m_{ij}^{l}} \} \}.$$
 (9)

In particular, if $\sum_{j} n_{ij}^l / \sum_{j} m_{ij}^l \equiv k \text{ (constant)}$, $\rho(H) = ||H||_{\infty} = k$. If $\sum_{j} n_{ij}^l / \sum_{j} m_{ij}^l \not\equiv \text{ constant and } H$ is irreducible, the two middle inequalities are strict.

Proof. The first part is obtained from theorem 1 and 2, while the second part can be obtained from theorem 9 in §1.3 of [6].

Corollary 2 ([4, 5]). Under the assumptions of theorem 2, we have

$$\min_{i} \left\{ \sum_{j} \frac{n_{ij}}{\sum_{j} m_{ij}} \right\} \leq \min_{i} \left\{ \sum_{j} (M^{-1}N)_{ij} \right\} \leq \rho(M^{-1}N) \leq \|M^{-1}N\|_{\infty}$$

$$= \max_{i} \left\{ \sum_{j} (M^{-1}N)_{ij} \right\} \leq \max_{i} \left\{ \sum_{j} \frac{n_{ij}}{\sum_{j} m_{ij}} \right\}. \tag{10}$$

Proof. We obtain (10) from corollary 1 taking k = 1 and $M_1 = M, N_1 = N$. We can get a further direct result from theorem 1.

Corollary 3. If M_l , N_l satisfy

$$|m_{ii}^l| \ge \sum_{j \ne i} |m_{ij}^l| + \sum_j |n_{ij}^l| \qquad i = 1, 2, \cdots, n$$
 (11)

and

$$|m_{ii}^l| > \sum_{i \neq i} |m_{ij}^l|;$$
 $i = 1, 2, \dots, n,$ (12)

then

$$\rho(H) \le \parallel H \parallel_{\infty} \le 1. \tag{13}$$

The second inequality in (13) will be strict when the inequality (11) is strict. The PMI-method is then convergent.

Numerical Examples

Consider the systems of linear equations (1), where

$$A = \begin{bmatrix} 5 & -2 & -2 \\ -4 & 10 & -4 \\ -2 & -2 & 5 \end{bmatrix}; b = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}.$$

We split A into several two-splittings as follows

(a)
$$M_1 = \begin{bmatrix} 5 & -1 & -1 \\ -2 & 10 & -2 \\ -1 & -1 & 5 \end{bmatrix}; M_2 = \begin{bmatrix} 5 & -2 & 0 \\ -4 & 10 & 0 \\ 0 & -2 & 5 \end{bmatrix};$$

$$N_1 = M_1 - A$$
; $N_2 = M_2 - A$; $E_1 = \text{diag}(0, 0, 1)$; $E_2 = \text{diag}(1, 1, 0)$;

- (b) Take M_1, M_2, N_1, N_2 as in (a) and take $E_1 = \text{diag}(1, 0, 0); E_2 = \text{diag}(0, 1, 1);$ (c) Take M_1, N_1, E_1, E_2 as in (a) and take $M_2 = \text{diag}(5, 10, 5); N_2 = M_2 A$.
- It follos from Corollary 2 that

$$\begin{array}{ll} \rho(H)=2/3 & \text{for case (a) and case (b),} \\ 2/3<\rho(H)<4/5 & \text{for case (c).} \end{array}$$

In fact, we get from practical computing that

- (a) $\det(\lambda I H) = \lambda(3\lambda 2)(9\lambda + 5)/27$ and $\rho(H) = 2/3$,
- (b) $\det(\lambda I H) = (3\lambda 2)(6\lambda + 1)(18\lambda + 5)/972$ and $\rho(H) = 2/3$,
- (c) $\det(\lambda I H) = (5\lambda + 2)(15\lambda^2 6\lambda 4)/75$ and $2/3 < \rho(H) = (6 + \sqrt{276})/30 \approx 22.61/30 < 4/5$

Applications

In this section, we give some convergence and divergence theorems of relaxed PMImethods by using the estimates established in §2. In order to do this, the concepts of optimally scaled matrix and its several properties introduced in [5] are useful.

Lemma 1 ([5]). Let $A = (a_{ij})$ be airreducible matrix with nonzero diagonal entries, D = diag(A), B = D - A. Then there exists a diagonal matrix $Q = diag(q_1, q_2, \dots, q_n)$ with positive diagonal entries such that $\stackrel{\sim}{A} = (\stackrel{\sim}{a}_{ij}) = AQ$,

$$\sum_{j \neq i} |\widetilde{a}_{ij}| / |\widetilde{a}_{ii}| = \rho(|D|^{-1}|B|) \qquad i = 1, 2, \dots, n$$
 (14)

here $\stackrel{\sim}{A}$ is unique except for a constant factor. Furthermore, for an arbitrary $\stackrel{\sim}{A}=(\stackrel{\sim}{a}_{ij})$ $= \stackrel{\sim}{A} P$ where $P = diag(p_1, p_2, \dots, p_n)$ with $0 < p_i \not\equiv constant$ for $i = 1, 2, \dots, n$, we have

$$\min_{i} \{ \sum_{j \neq i} || \bar{a}_{ij} |/| \bar{a}_{ii} || \} \le \rho(|D|^{-1}|B|) \le \max_{i} \{ \sum_{j \neq i} || \bar{a}_{ij} |/| \bar{a}_{ii} || \}.$$
 (15)

We call \tilde{A} the optimally scaled matrix of A. Several properties can be established

Property 1 ([5]). Under the assumptions of lemma 1, we have

$$\rho(|\stackrel{\sim}{D}|^{-1}|\stackrel{\sim}{B}|) = ||\stackrel{\sim}{D}|^{-1}|\stackrel{\sim}{B}||_{\infty} = \rho(|D|^{-1}|B|)$$

where $\tilde{D} = \operatorname{diag}(\tilde{A}), \tilde{B} = \tilde{D} - \tilde{A}$.

Property 2 ([5]). Under the assumptions of lemma 1, the following four properties are equivalent.

(a)
$$\rho(|D|^{-1}|B|) < 1$$
, (b) $\rho(|\stackrel{\sim}{D}|^{-1}|\stackrel{\sim}{B}|) < 1$

 $\begin{array}{ll} (a)\; \rho(|D|^{-1}|B|) < 1, & (b)\; \rho(\mid \stackrel{\sim}{D}\mid^{-1}\mid \stackrel{\sim}{B}\mid) < 1, \\ (c)\; A \text{ is H-matrix, i. e., } \langle A\rangle \text{ is M-matrix,} & (d)\; \stackrel{\sim}{A} \text{ is H-matrix, i.e.,} \langle \stackrel{\sim}{A}\rangle \text{ is M-matrix} \;. \end{array}$

And if one of the above holds, \tilde{A} is SDD, i.e., $\mid \tilde{a}_{ii} \mid > \sum_{i \neq i} \mid \tilde{a}_{ij} \mid$.

Property 3 ([5]). Under the assumptions of lemma 1, if A and \tilde{A} have matrix splittings A = M - N; $\widetilde{A} = \widetilde{M} - \widetilde{N}$ where $\widetilde{M} = MQ$, $\widetilde{N} = NQ$, M^{-1} exists. Here Qis given in lemma 1. Then

$$\rho(M^{-1}N) = \rho(\widetilde{M}^{-1}\widetilde{N}). \tag{16}$$

Let $(D - L_l, U_l, E_l)$ be a multisplitting of A, where D = diag(A), L_l is strictly lower triangular. Let $R = \operatorname{diag}(r_1, r_2, \dots, r_n), \Omega = \operatorname{diag}(\omega_1, \omega_2, \dots, \omega_n)$ be relatation matrices, where $r_i \geq 0, \omega_i > 0$ for $i = 1, 2, \dots, n$ and let $\omega > 0, r \geq 0$. We can then write the iterative matrices of PMI-SOR [2], PMI-GSOR [3], PMI-AOR [10] and

PMI-GAOR [3] as follows:

$$\pounds_{\omega}(A) = \sum_{l} E_{l}(D - \omega L_{l})^{-1} [(1 - \omega)D + \omega U_{l}],$$

$$\pounds_{\Omega}(A) = \sum_{l} E_{l}(D - \Omega L_{l})^{-1} [(I - \Omega)D + \Omega U_{l}],$$

$$\pounds_{r,\omega}(A) = \sum_{l} E_{l}(D - rL_{l})^{-1} [(1 - \omega)D + (\omega - r)L_{l} + \omega U_{l}],$$

$$\pounds_{R,\Omega}(A) = \sum_{l} E_{l}(D - RL_{l})^{-1} [(I - \Omega)D + (\Omega - R)L_{l} + \Omega U_{l}].$$

If we let $D = \operatorname{diag}(A)$, B = D - A, then the Jacobi iterative matrix is $J(A) = D^{-1}B$. We denote the intervals $\left(0, \frac{2}{1+\rho(J(A))}\right)$ and $\left[0, \frac{2}{1+\rho(J(A))}\right)$ as I_A and \widetilde{I}_A , respectively. We then have the following theorem.

Theorem 3. Let A be an H-matrix with $\langle A \rangle = D - |L_l| - |U_l|$. Then

- (a) $\rho(\pounds_{\omega}(A)) < 1, \forall \omega \in I_A$.
- (b) $\rho(\pounds_{\Omega}(A)) < 1, \forall \omega_i \in I_A(\forall i).$
- (c) $\rho(\pounds_{r,\omega}(A)) < 1$, $\forall r \leq \omega, r \in I_A, \omega \in I_A$.
- (d) $\rho(\pounds_{R,\Omega}(A)) < 1$, $\forall r_i \leq \omega_i, r_i \in I_A, \omega_i \in I_A(\forall i)$.

Proof. Since (a), (b), (c) are special cases of (d), we only give a proof of (d). We

first assume that A is irreducible. Hence, by theorem 1, we have

$$\rho(\pounds_{R,\Omega}(A)) = \rho(\pounds_{R,\Omega}(\widetilde{A})) \le || \pounds_{R,\Omega}(\widetilde{A}) ||_{\infty}
\le \max_{l} \{ \max_{i} \{ \frac{|1-\omega_{i}||\widetilde{a}_{ii}| + (\omega_{i}-r_{i}) \sum_{j < i} |l_{ij}^{l}| + +\omega_{i} \sum_{j} |u_{ij}^{l}|}{\widetilde{a}_{ii}-r_{i} \sum_{j < i} |l_{ij}^{l}|} \} \}
= \max_{l} \{ \max_{i} \{ \frac{|1-\omega_{i}| + \omega_{i}\rho(|J(A)|) - r_{i} \sum_{j < i} |l_{ij}^{l}| / |\widetilde{a}_{ii}|}{1 - r_{i} \sum_{j < i} |l_{ij}^{l}| / |\widetilde{a}_{ii}|} \} \}.$$
(17)

When $\omega_i \in I_A$ for $i = 1, 2, \dots, n$, we obtain $|1 - \omega_i| + \omega_i \rho(|J(A)|) < 1$. When a, b, c > 0, a < b, we have (a - c)/(b - c) < a/b. Hence, when $r_i \leq \omega_i, r_i \in I_A, \omega_i \in I_A(\forall i)$, we get from (17) that

$$\rho(\pounds_{R,\Omega}(\widetilde{A})) = \rho(\pounds_{R,\Omega}(A)) < |1 - \omega_i| + \omega_i \rho(|J(A)|) < 1.$$

If A is reducible, we can change some zero entries of A into sufficient a small positive number $\epsilon > 0$ such that A change into A_{ϵ} and A_{ϵ} is irreducible. We can work with A_{ϵ} as above. Finally, we can show that theorem 3 holds when A is reducible by taking $\epsilon \to 0$ and using the continuity of the spectral radius of the entries of the matrix.

Remark. Theorem 3 shows that PMI-SOR, PMI-GSOR, PMI-AOR and PMI-GAOR are convergent if the parameters are in the intervals given in theorem 3. This is in keeping with results given in [2], [3], [10]. We unify the proof of convergence of these relaxed PMI-methods. Using theorem 1, we can get more general results than those given in [2], [3], [10] and theorem 3.

Theorem 4. If A is SDD, $\langle A \rangle = |D| - |L_l| - |U_l|$ and $\omega > 0, \omega_i > 0, 0 \le r \le \omega, 0 \le r_i \le \omega_i$ for $i = 1, 2, \dots, n$ are all smaller than $2|a_{ii}|/\sum_i |a_{ij}|$, then all relaxed

PMI-methods in theorem 3 are convergent.

Theorem 5. If A is an irreducible L-matrix but not a M-matrix, then

- (a) $\rho(\pounds_{\omega}(A)) \geq 1$ for sufficiently small ω .
- (b) $\rho(\pounds_{\Omega}(A)) \geq 1$ for sufficiently small $\omega_i(\forall i)$.
- (c) $\rho(\mathcal{L}_{r,\omega}(A)) \geq 1$ for sufficiently small r,ω with $0 \leq r \leq \omega$.
- (d) $\rho(\pounds_{R,\Omega}(A)) \geq 1$ for suitable small r_i, ω_i with $0 \leq r_i \leq \omega_i(\forall i)$.

Proof. We also only show that (d) holds. First, we choose r_i sufficiently small such that $D - RL_l$ is SDD. Then we have from theorem 2 and property 3, that

$$\rho(\pounds_{R,\Omega}(A)) = \rho(\pounds_{R,\Omega}(\widetilde{A}))$$

$$\geq \min_{l} \{ \min_{i} \{ \frac{[1 - \omega_{i}] + \omega_{i}\rho(|J(A)|) - r_{i} \sum_{j < i} |l_{ij}^{l}|/|\widetilde{a}_{ii}|}{1 - r_{i} \sum_{j < i} |l_{ij}^{l}|/|\widetilde{a}_{ii}|} \} \}$$
(18)

and from property 2, we get that the right hand of inequality (18) is not smaller than unit for any l and i. So (d) holds.

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