

An improvement of H. Wang preconditioner for L -matrices

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Abstract

In this paper, we improve the preconditioner, that introduced by H. Wang et al [6]. The H. Wang preconditioner $P \in \mathbb{R}^{n \times n}$ has only one non-zero, non-diagonal element in $P(n, 1)$ or $P(1, n)$, when $a_{(1,n)}a_{(n,1)} \neq 0$. But the new preconditioner has only one non-zero, non-diagonal element in $P(i, j)$ or $P(j, i)$ if $a_{(i,j)}a_{(j,i)} \neq 0$, so the H. Wang preconditioner is a special case of the new preconditioner for L -matrices. Also we present two models to construct a better $I + S$ type preconditioner for the AOR iterative method. Convergence analysis are given, numerical results are presented which show the effectiveness of the new preconditioners.

Keywords: Linear system; AOR method; Jacobi method; Gauss-Seidel method; Spectral radius; M -matrix; L -matrix; Preconditioner.

1. Introduction

Consider the following linear system

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

where $A \in \mathbb{R}^{n \times n}$, $b \in \mathbb{R}^n$ are given and $x \in \mathbb{R}^n$ is unknown. For simplicity, suppose that

$$A = I - L - U, \tag{2}$$

where I is identity matrix and $-L$ and $-U$ are strictly lower and upper triangular parts of matrix A , respectively. The accelerated overrelaxation(AOR) iterative method [3] is given by,

$$x^{(i+1)} = L_{\gamma, \omega} x^{(i)} + (I - \gamma L)^{-1} \omega b, \quad i = 0, 1, 2, \dots, \tag{3}$$

whose iteration matrix is

$$L_{\gamma, \omega} = (I - \gamma L)^{-1} [(1 - \omega)I + (\omega - \gamma)L + \omega U], \tag{4}$$

where ω and γ are real parameters with $\omega \neq 0$.

Now, let us consider the preconditioned linear system,

$$PAx = Pb, \tag{5}$$

where $P = I + S$ is a nonsingular matrix and $S \in \mathbb{R}^{n \times n}$. For L -matrices linear systems, first, Evans et al [2] proposed the preconditioned matrix $P = I + S$, where

$$S = \begin{pmatrix} 0 & 0 & \dots & 0 \\ 0 & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ -a_{n1} & 0 & \dots & 0 \end{pmatrix} \in \mathbb{R}^{n \times n}, \tag{6}$$

or $S = \begin{pmatrix} 0 & 0 & \dots & -a_{1n} \\ 0 & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 0 \end{pmatrix} \in \mathbb{R}^{n \times n}.$

This preconditioners has been studied by Yun [9] and Li et al [4]. recently H. wang et al [6] provided a preconditioner and improved the convergence rate of the AOR iterative method. They considered

$$S_{\alpha\beta} = \begin{pmatrix} 0 & 0 & \dots & 0 \\ 0 & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ \frac{-a_{n1}}{\alpha} - \beta & 0 & \dots & 0 \end{pmatrix} \in \mathbb{R}^{n \times n} \tag{7}$$

or $S_{\alpha\beta} = \begin{pmatrix} 0 & 0 & \dots & \frac{-a_{1n}}{\alpha} - \beta \\ 0 & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 0 \end{pmatrix} \in \mathbb{R}^{n \times n}.$

But if, $a_{1n}a_{n1} = 0$ these preconditioners are invalid. For solve this problem, we suggest the new preconditioner as follow.

2. Improvement of the H. Wang preconditioner

Consider the following linear system

$$\tilde{A}x = \tilde{b}, \tag{8}$$

where $\tilde{A} = (I + \tilde{S}_{\alpha\beta rt})A$ and $\tilde{b} = (I + \tilde{S}_{\alpha\beta rt})b$, with $\tilde{S}_{\alpha\beta rt} \in \mathbb{R}^{n \times n}$ and for $i, j = 1, \dots, n$

$$(\tilde{S}_{\alpha\beta rt})_{ij} = \begin{cases} \frac{-a_{rt}}{\alpha} - \beta, & i = r, j = t, \\ 0, & \text{otherwise.} \end{cases} \tag{9}$$

Here, $\alpha, \beta \in \mathbb{R}$ and $r, t \in N = \{1, 2, \dots, n\}$, $r \neq t$. Clearly $(I + \tilde{S}_{\alpha\beta rt})$ is an nonsingular matrix.

The elements \tilde{a}_{ij} of \tilde{A} are given by the expression

$$\tilde{a}_{ij} = \begin{cases} a_{ij}, & i \neq r, \\ a_{rt}(1 - \frac{1}{\alpha}) - \beta & i = r, j = t, \\ a_{rj} - (\frac{a_{rt}}{\alpha} + \beta)a_{tj} & i = r, j \neq t. \end{cases} \quad i, j = 1, \dots, n \tag{10}$$

Since $A = I - L - U$, we have, $\tilde{a}_{rr} = 1 - (\frac{a_{rt}}{\alpha} + \beta)a_{tr}$ and also, if we put

$$\tilde{A} = \tilde{D} - \tilde{L} - \tilde{U}, \tag{11}$$

where \tilde{D} is diagonal matrix and $-\tilde{L}$ and $-\tilde{U}$ are strictly lower and upper triangular parts of matrix \tilde{A} , respectively. We have

$$\begin{aligned} \tilde{A} &= (I + \tilde{S}_{\alpha\beta rt})A \\ &= (I + \tilde{S}_{\alpha\beta rt})(I - L - U) \\ &= I + \tilde{S}_{\alpha\beta rt}L - L - U - \tilde{S}_{\alpha\beta rt}L - \tilde{S}_{\alpha\beta rt}U. \end{aligned} \tag{12}$$

If $r > t$, put

$$\tilde{S}_{\alpha\beta rt}U = \tilde{D} + \tilde{L} + \tilde{U}, \tag{13}$$

where \tilde{D} is diagonal matrix and \tilde{L} and \tilde{U} are strictly lower and upper triangular parts of matrix $\tilde{S}_{\alpha\beta rt}U$, respectively. So

$$\tilde{A} = (I - \tilde{D}) - (L + \tilde{S}_{\alpha\beta rt}L - \tilde{S}_{\alpha\beta rt}\tilde{L}) - (U + \tilde{U}) = \tilde{D} - \tilde{L} - \tilde{U}$$

where,

$$\tilde{D} = I - \tilde{D}, \tilde{L} = L + \tilde{S}_{\alpha\beta rt}L - \tilde{S}_{\alpha\beta rt}\tilde{L} \text{ and } \tilde{U} = U + \tilde{U}. \tag{14}$$

If $r < t$, put

$$\tilde{S}_{\alpha\beta rt}L = \tilde{D} + \tilde{L} + \tilde{U}, \tag{15}$$

so,

$$\tilde{A} = (I - \tilde{D}) - (L + \tilde{L}) - (U + \tilde{S}_{\alpha\beta rt}U - \tilde{S}_{\alpha\beta rt}\tilde{U}) = \tilde{D} - \tilde{L} - \tilde{U}$$

where,

$$\tilde{D} = I - \tilde{D}, \tilde{L} = L + \tilde{L} \text{ and } \tilde{U} = U + \tilde{S}_{\alpha\beta rt}U - \tilde{S}_{\alpha\beta rt}\tilde{U} \tag{16}$$

The AOR iterative method for the preconditioned system (8) is given by

$$x^{(i+1)} = \tilde{L}_{\gamma,\omega}^{r,t}x^{(i)} + (\tilde{D} - \gamma\tilde{L})^{-1}\omega(I + \tilde{S}_{\alpha\beta rt})b, \quad i = 0, 1, 2, \dots, \tag{17}$$

whose iteration matrix is

$$\tilde{L}_{\gamma,\omega}^{r,t} = (\tilde{D} - \gamma\tilde{L})^{-1}[(1 - \omega)\tilde{D} + (\omega - \gamma)\tilde{L} + \omega\tilde{U}], \tag{18}$$

where ω and γ are real parameters with $\omega \neq 0$.

3. Convergence analysis

In the sequel, we need the following. Let $A, B \in \mathbb{R}^{n \times n}$. If $a_{ij} \geq b_{ij}$ ($a_{ij} > b_{ij}$), $i, j = 1, 2, \dots, n$, we write $A \geq B$ ($A > B$). The same notation applies to vectors $x, y \in \mathbb{R}^n$. If $A \in \mathbb{R}^{n \times n}$ satisfies $A \geq 0$ (> 0) then it is said to be *nonnegative (positive)*. The same terminology applies to vectors $x \in \mathbb{R}^n$. (see [8].) A matrix $A \in \mathbb{R}^{n \times n}$ is said to be an *L-matrix* if $a_{ii} > 0$, $i = 1, 2, \dots, n$, and $a_{ij} \leq 0$, $i \neq j = 1, 2, \dots, n$. (see [5].) A matrix $A \in \mathbb{R}^{n \times n}$ is said to be an *M-matrix* if $a_{ij} \leq 0$, $i \neq j = 1, 2, \dots, n$, A is nonsingular and $A^{-1} \geq 0$. (see [5].) A matrix A is said to be *irreducible* if the directed graph associated with A is strongly connected. (see [5].) Let $A \geq 0$ then:

1. A has positive real eigenvalue equal to its spectral radius $\rho(A)$;
2. A has an eigenvector $x \geq 0$, with at least a positive entry, corresponding to $\rho(A)$;
3. If A is irreducible, then $\rho(A)$ is a simple eigenvalue of A and A has an eigenvector $x > 0$ corresponding to $\rho(A)$.

(see [5].) Let $A \geq 0$ then:

1. If $\alpha x \leq Ax$ for some $x \geq 0$, with at least a positive entry, then $\alpha \leq \rho(A)$;
2. If $Ax \leq \beta x$ for some $x > 0$, then $\rho(A) \leq \beta$. Moreover, if A is irreducible and if $Ax \leq \beta x$ for some $x \geq 0$, then $\rho(A) \leq \beta$ and $x > 0$.
3. If A is irreducible and if $\alpha x \leq Ax \leq \beta x$ for some $x > 0$, then $\alpha \leq \rho(A) \leq \beta$.

Let A and \tilde{A} be the coefficient matrices of the linear systems (1) and (8), respectively. If $0 \leq \gamma \leq \omega \leq 1$ ($\omega \neq 0$ and $\gamma \neq 1$) and A is an irreducible *L-matrix* with $0 < a_{rt}a_{tr} < \alpha(\alpha > 1)$, $\beta \in (\frac{-a_{rt}}{\alpha} + \frac{1}{a_{tr}}, \frac{-a_{rt}}{\alpha}) \cap ((1 - \frac{1}{\alpha})a_{rt}, \frac{-a_{rt}}{\alpha})$ then the iterative matrices $L_{\gamma,\omega}$ and $\tilde{L}_{\gamma,\omega}^{r,t}$ associated to the AOR method applied to the linear systems (1) and (8), respectively, are nonnegative and irreducible. Moreover \tilde{A} is an irreducible *L-matrix*.

Proof. It is easy to see that when $a_{rt}a_{tr} < \alpha(\alpha > 1)$ and $\beta \in (\frac{-a_{rt}}{\alpha} + \frac{1}{a_{tr}}, \frac{-a_{rt}}{\alpha}) \cap ((1 - \frac{1}{\alpha})a_{rt}, \frac{-a_{rt}}{\alpha})$, we have $\tilde{a}_{rr} = 1 - (\frac{a_{rt}}{\alpha} + \beta)a_{tr} > 0$ and $\frac{a_{rt}}{\alpha} + \beta < 0$ so, $\tilde{a}_{ij} = a_{rj} - (\frac{a_{rt}}{\alpha} + \beta)a_{tj} < 0$ (for $i = r$ and $j \neq t$), and also $\tilde{a}_{rt} = a_{rt}(1 - \frac{1}{\alpha}) - \beta < 0$, so \tilde{A} is an *L-matrix* and the directed graph associated to A is a subgraph of the directed graph associated to \tilde{A} , then Since A is irreducible \tilde{A} is irreducible too. Also from (11), we have $\tilde{D} > 0$, $\tilde{L} \geq 0$ and $\tilde{U} \geq 0$. The rest of proof is similar to the Lemma 3 in [6]. \square

Note1:

When A is an *L-matrix* then under the assumptions of Lemma 3, $\tilde{S}_{\alpha\beta rt} \geq 0$.

Let $L_{\gamma,\omega}$ and $\tilde{L}_{\gamma,\omega}^{r,t}$ be the iteration matrices of the AOR method applied to the linear systems (1) and (8), respectively. If $0 \leq \gamma \leq \omega \leq 1$ ($\omega \neq 0$ and $\gamma \neq 1$) and A is an irreducible *L-matrix* with $0 < a_{rt}a_{tr} < \alpha(\alpha > 1)$, $\beta \in (\frac{-a_{rt}}{\alpha} + \frac{1}{a_{tr}}, \frac{-a_{rt}}{\alpha}) \cap ((1 - \frac{1}{\alpha})a_{rt}, \frac{-a_{rt}}{\alpha})$, then:

1. $\rho(\tilde{L}_{\gamma,\omega}^{r,t}) \leq \rho(L_{\gamma,\omega})$, if $\rho(L_{\gamma,\omega}) < 1$;
2. $\rho(\tilde{L}_{\gamma,\omega}^{r,t}) = \rho(L_{\gamma,\omega}) = 1$;
3. $\rho(\tilde{L}_{\gamma,\omega}^{r,t}) \geq \rho(L_{\gamma,\omega})$, if $\rho(L_{\gamma,\omega}) > 1$.

Proof. From Lemmas 3, 3 and 3, since $L_{\gamma,\omega}$ and $\tilde{L}_{\gamma,\omega}^{r,t}$ are nonnegative and irreducible matrices, there is a positive vector $x > 0$, such that

$$L_{\gamma,\omega}x = \lambda x, \tag{19}$$

where $\rho(L_{\gamma,\omega}) = \lambda$. Equivalently, we can write

$$[(1 - \omega)I + (\omega - \gamma)L + \omega U]x = \lambda(I - \gamma L)x, \tag{20}$$

and also, we have

$$\omega Ux = (\lambda - 1 + \omega)x + (\gamma - \omega - \lambda\gamma)Lx. \tag{21}$$

On the other hand, for the positive vector x we have,

$$\tilde{L}_{\gamma,\omega}^{r,t}x - \lambda x = (\tilde{D} - \gamma\tilde{L})^{-1}[(1 - \omega)\tilde{D} + (\omega - \gamma)\tilde{L} + \omega\tilde{U} - \lambda(\tilde{D} - \gamma\tilde{L})]x. \tag{22}$$

Case(1): If $r > t$, from (14), since $\tilde{U} = U + \tilde{U}$ and from (21) we have,

$$\omega\tilde{U}x = \omega(U + \tilde{U})x = (\lambda - 1 + \omega)x + (\gamma - \omega - \lambda\gamma)Lx + \omega\tilde{U}x, \tag{23}$$

and also

$$\begin{aligned} & \lambda(\tilde{D} - \gamma\tilde{L})x = \\ & \lambda(1 - \gamma)\tilde{D}x + \lambda\gamma(\tilde{D} - \tilde{L})x = \\ & \lambda(1 - \gamma)\tilde{D}x + \lambda\gamma(I + \tilde{S}_{\alpha\beta rr} - L - \tilde{S}_{\alpha\beta rr}U + \tilde{U} - \tilde{S}_{\alpha\beta rr}L)x. \end{aligned} \tag{24}$$

From (22), (23) and (24), we have

$$\begin{aligned} & \tilde{L}_{\gamma,\omega}^{r,t}x - \lambda x = \\ & (\tilde{D} - \gamma\tilde{L})^{-1}[(1 - \gamma)(1 - \lambda)(\tilde{D} - I) + (\omega - \gamma + \lambda\gamma)(\tilde{S}_{\alpha\beta rr}U - \tilde{S}_{\alpha\beta rr})x \\ & + (\omega - \gamma + \lambda\gamma)\tilde{S}_{\alpha\beta rr}L - (\lambda\gamma - \gamma)\tilde{U}]x, \end{aligned}$$

again from (21) we have

$$\tilde{L}_{\gamma,\omega}^{r,t}x - \lambda x = (1 - \lambda)(\tilde{D} - \gamma\tilde{L})^{-1}[(\gamma - 1)\tilde{D} - (1 - \gamma)\tilde{S}_{\alpha\beta rr} - \gamma(\tilde{D} + \tilde{L})]x.$$

Put $B = (\gamma - 1)\tilde{D} - (1 - \gamma)\tilde{S}_{\alpha\beta rr} - \gamma(\tilde{D} + \tilde{L})$, from (13) and Note1, we conclude that, $B \leq 0$. So if $\lambda < 1$ then $z = (1 - \lambda)(\tilde{D} - \gamma\tilde{L})^{-1}Bx$ is nonpositive vector, and $\tilde{L}_{\gamma,\omega}^{r,t}x \leq \lambda x$, so from Lemma 3 we obtain

$$\rho(\tilde{L}_{\gamma,\omega}^{r,t}) \leq \lambda = \rho(L_{\gamma,\omega}) < 1.$$

And if $\lambda = 1$, then $z = 0$ and $\tilde{L}_{\gamma,\omega}^{r,t}x = \lambda x$, from Lemma 3 we obtain,

$$\rho(\tilde{L}_{\gamma,\omega}^{r,t}) = \lambda = \rho(L_{\gamma,\omega}) = 1,$$

Finally if, $\lambda > 1$, then z will be nonnegative vector and $\tilde{L}_{\gamma,\omega}^{r,t}x \geq \lambda x$, again from Lemma 3 we obtain,

$$\rho(\tilde{L}_{\gamma,\omega}^{r,t}) \geq \lambda = \rho(L_{\gamma,\omega}) > 1.$$

Case(2): If $r < t$, from (16) and (22) we have

$$\begin{aligned} & \tilde{L}_{\gamma,\omega}^{r,t}x - \lambda x = \\ & (\tilde{D} - \gamma\tilde{L})^{-1}[(1 - \lambda)\tilde{D} - \gamma(1 - \lambda)\tilde{L} - \omega(\tilde{D} - \tilde{U}) + \omega\tilde{L}]x = \\ & (\tilde{D} - \gamma\tilde{L})^{-1}[(1 - \lambda)\tilde{D} - \gamma(1 - \lambda)L - \omega(I + \tilde{S}_{\alpha\beta rr} - \tilde{S}_{\alpha\beta rr}L - U) \\ & + \omega L - \gamma(1 - \lambda)\tilde{L} - \omega(\tilde{L} - \tilde{S}_{\alpha\beta rr}U) + \omega\tilde{L}]x = \\ & (\tilde{D} - \gamma\tilde{L})^{-1}[(1 - \lambda)(\tilde{D} - I) - \omega(\tilde{S}_{\alpha\beta rr} - \tilde{S}_{\alpha\beta rr}L) - \gamma(1 - \lambda)\tilde{L} + \\ & \omega\tilde{S}_{\alpha\beta rr}U]x = \\ & (\tilde{D} - \gamma\tilde{L})^{-1}[(1 - \lambda)(\tilde{D} - I) + (\lambda - 1)\tilde{S}_{\alpha\beta rr}(I - \gamma L) - \gamma(1 - \lambda)\tilde{L}]x \end{aligned}$$

from (20) we have

$$\begin{aligned} & \tilde{L}_{\gamma,\omega}^{r,t}x - \lambda x = \\ & (\lambda - 1)(\tilde{D} - \gamma\tilde{L})^{-1}[\tilde{D} + \frac{1}{\lambda}\tilde{S}_{\alpha\beta rr}[(1 - \omega)I + (\omega - \gamma)L + \omega U] + \gamma\tilde{L}]x. \end{aligned}$$

Put $E = \tilde{D} + \frac{1}{\lambda}\tilde{S}_{\alpha\beta rr}[(1 - \omega)I + (\omega - \gamma)L + \omega U] + \gamma\tilde{L}$, Clearly, E is nonnegative matrix, so if $\lambda < 1$, $g = (\lambda - 1)(\tilde{D} - \gamma\tilde{L})^{-1}Ex \leq 0$, and $\tilde{L}_{\gamma,\omega}^{r,t}x \leq \lambda x$ and from Lemma 3 we have

$$\rho(\tilde{L}_{\gamma,\omega}^{r,t}) \leq \lambda = \rho(L_{\gamma,\omega}) < 1.$$

The rest of proof is in similar way with case (1). \square

Let L_{GS} and $\tilde{L}_{GS}^{r,t}$ be the iteration matrices of the Gauss-Seidel method applied to the linear systems (1) and (8), respectively. If A is a nonsingular irreducible M -matrix with $0 < a_{rr} < \alpha(\alpha > 1)$, $\beta \in (\frac{-a_{rr}}{\alpha} + \frac{1}{a_{rr}}, \frac{-a_{rr}}{\alpha}) \cap ((1 - \frac{1}{\alpha})a_{rr}, \frac{-a_{rr}}{\alpha})$, then \tilde{A} is an irreducible M -matrix and :

1. $\rho(\tilde{L}_{GS}^{r,t}) \leq \rho(L_{GS})$, if $\rho(L_{GS}) < 1$;
2. $\rho(\tilde{L}_{GS}^{r,t}) = \rho(L_{GS}) = 1$;
3. $\rho(\tilde{L}_{GS}^{r,t}) \geq \rho(L_{GS})$, if $\rho(L_{GS}) > 1$.

Proof. Same as Lemma 3, it is clear that \tilde{A} is an irreducible L -matrix. For a L -matrix A the statement " A is a nonsingular M -matrix " is equivalent to the statement " there exists a positive vector $y \in \mathbb{R}^n$ ($y > 0$) such that $Ay > 0$ " (see Theorem 6.2.3. Condition I_{27} of [1]). But $P = I + \tilde{S}_{\alpha\beta rr} \geq 0$ implies that $\tilde{A}y = PAy > 0$ so \tilde{A} is an M -matrix too. From Theorem 2.6. in [7] the rest of proof is trivial. \square

4. Models for Selecting r and t

Consider how to select r and t to construct a better $I + S$ type preconditioner. Now we state the two following Lemmas, we use these Lemmas to construct a better $I + S$ preconditioners. (see [5].) If $A = (a_{i,j}) \geq 0$, is an irreducible $n \times n$ matrix the either

$$\sum_{j=1}^n a_{i,j} = \rho(A) \text{ for all } 1 \leq i \leq n$$

$$\min_{1 \leq i \leq n} (\sum_{j=1}^n a_{i,j}) < \rho(A) < \max_{1 \leq i \leq n} (\sum_{j=1}^n a_{i,j})$$

If $A = (a_{i,j}) \geq 0$, is an irreducible $n \times n$ matrix the either

$$\sum_{i=1}^n a_{i,j} = \rho(A) \text{ for all } 1 \leq j \leq n$$

$$\min_{1 \leq j \leq n} (\sum_{i=1}^n a_{i,j}) < \rho(A) < \max_{1 \leq j \leq n} (\sum_{i=1}^n a_{i,j})$$

Proof. Since $\rho(A) = \rho(A^T)$ and $A^T \geq 0$ is an irreducible $n \times n$ matrix, so from Lemma 4, the proof is trivial. \square

If $L_{\gamma,\omega}$ and $\tilde{L}_{\gamma,\omega}^{r,t}$ be the iteration matrices of the AOR method applied to the linear systems (1) and (8), respectively, we write $(L_{\gamma,\omega})_{i,j} = (l_{i,j})$ and $(\tilde{L}_{\gamma,\omega}^{r,t})_{i,j} = (l_{i,j}^{r,t})$ for $i, j = 1, \dots, n$ when $P = (I + \tilde{S}_{\alpha\beta rr})$. Now, suppose that γ and $\omega \in \mathbb{R}$, $\omega \neq 0$ be two fixed parameters, from Lemma 4, we select r such that

$$\sum_{j=1}^n l_{r,j} = \max_{1 \leq i \leq n} (\sum_{j=1}^n l_{i,j}).$$

For selecting t , we present two models.

Model1:

$$\sum_{j=1}^n l_{r,j}^{r,t} = \min_{1 \leq k \leq n} (\sum_{j=1}^n l_{r,j}^{r,k}), \quad k \neq r.$$

Model2:

$$\sum_{i=1}^n l_{i,t} = \max_{1 \leq j \leq n} (\sum_{i=1}^n l_{i,j}).$$

Note2:

Selecting r and t in Model2 are not depend on α and β , but not Model1. So here we suppose that α and β are two arbitrary parameters that satisfy in conditions of Lemma 3.

Now for computing r and t put $e = (1, 1, \dots, 1)^T \in \mathbb{R}^n$, it is easy to see that

$$(L_{\gamma,\omega}e)_i = \sum_{j=1}^n l_{i,j}, \tag{25}$$

and

$$\max_{1 \leq i \leq n} (\sum_{j=1}^n l_{i,j}) = (L_{\gamma,\omega}e)_r,$$

so we should compute $u_1 = L_{\gamma,\omega}e$, but from (4), we have

$$u_1 = (I - \gamma L)^{-1}[(1 - \omega)I + (\omega - \gamma)L + \omega U]e,$$

so if we put $b_1 = [(1 - \omega)I + (\omega - \gamma)L + \omega U]e$, computing u_1 is equivalent to solving the lower triangular system

$$(I - \gamma L)u_1 = b_1. \tag{26}$$

Model1:

Same as (25) we have

$$(\tilde{L}_{\gamma,\omega}^{r,k}e)_r = \sum_{j=1}^n l_{r,j}^{r,k},$$

so for $k = 1, 2, \dots, n$ we should compute $(\tilde{L}_{\gamma, \omega}^{r,k} e)_r$, but from (18) we put

$$u_2 = (\tilde{D} - \gamma \tilde{L})^{-1} [(1 - \omega) \tilde{D} + (\omega - \gamma) \tilde{L} + \omega \tilde{U}] e,$$

and

$$b_2 = [(1 - \omega) \tilde{D} + (\omega - \gamma) \tilde{L} + \omega \tilde{U}] e,$$

clearly, since only, $(\tilde{L}_{\gamma, \omega}^{r,k} e)_r$ is needed, so computing $b_2(r + 1 : n)$ is not necessary. Also since $(1 - \omega) \tilde{D} + (\omega - \gamma) \tilde{L} + \omega \tilde{U}$ differs with $(1 - \omega)I + (\omega - \gamma)L + \omega U$ in r th row, so $b_2(1 : r - 1) = b_1(1 : r - 1)$, and only we should compute $b_2(r)$. Since $\tilde{D} - \gamma \tilde{L}$ is different with $I - \gamma L$ in r th row and $b_2(1 : r - 1) = b_1(1 : r - 1)$ in the lower triangular system

$$(\tilde{D} - \gamma \tilde{L}) u_2 = b_2,$$

only need to compute $u_2(r)$, so

$$u_2(r) = [b_2(r) - (\tilde{D} - \gamma \tilde{L})(r, 1 : r - 1) u_1(1 : r - 1)] / (\tilde{D} - \gamma \tilde{L})(r, r).$$

Model2:

Here we should compute $u_3 = L_{\gamma, \omega}^T e$, from (4) we have

$$u_3 = [(1 - \omega)I + (\omega - \gamma)L + \omega U]^T ((I - \gamma L)^T)^{-1} e,$$

if we put $b_3 = ((I - \gamma L)^T)^{-1} e$, computing b_3 is equivalent to solving the upper triangular system $(I - \gamma L)^T b_3 = e$. Finally

$$u_3 = [(1 - \omega)I + (\omega - \gamma)L + \omega U]^T b_3.$$

These models when $\gamma = 0$ and $\omega = 1$ reduced to simpler models, for preconditioned Jacobi method (see[10]).

$$A_3 = \begin{pmatrix} 1 & -\frac{1}{n \times 1100} & -\frac{1}{(n-1) \times 1100} & \dots & -\frac{1}{3 \times 1100} & -\frac{1}{22} \\ -\frac{1}{n \times 10+1} & 1 & -\frac{1}{3 \times 10+2} & \dots & -\frac{1}{(n-1) \times 10+2} & -\frac{1}{n \times 10+2} \\ -\frac{1}{(n-1) \times 10+1} & -\frac{1}{2 \times 10+3} & 1 & \dots & -\frac{1}{(n-1) \times 10+3} & -\frac{1}{n \times 10+3} \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ -\frac{1}{3 \times 10+1} & -\frac{1}{(n-2) \times 10+(n-1)} & -\frac{1}{(n-3) \times 10+(n-1)} & \dots & 1 & -\frac{1}{n \times 10+(n-1)} \\ -\frac{100}{7} & -\frac{1}{(n-1) \times 10+n} & -\frac{1}{(n-2) \times 10+n} & \dots & -\frac{1}{2 \times 10+n} & 1 \end{pmatrix}$$

$$A_4 = \begin{pmatrix} 1 & -\frac{100}{7} & -\frac{1}{(n-1) \times 1100} & \dots & -\frac{1}{3 \times 1100} & 0 \\ -\frac{1}{22} & 1 & -\frac{1}{3 \times 10+2} & \dots & -\frac{1}{(n-1) \times 10+2} & -\frac{1}{n \times 10+2} \\ -\frac{1}{(n-1) \times 10+1} & -\frac{1}{2 \times 10+3} & 1 & \dots & -\frac{1}{(n-1) \times 10+3} & -\frac{1}{n \times 10+3} \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ -\frac{1}{3 \times 10+1} & -\frac{1}{(n-2) \times 10+(n-1)} & -\frac{1}{(n-3) \times 10+(n-1)} & \dots & 1 & -\frac{1}{n \times 10+(n-1)} \\ 0 & -\frac{1}{(n-1) \times 10+n} & -\frac{1}{(n-2) \times 10+n} & \dots & -\frac{1}{2 \times 10+n} & 1 \end{pmatrix}$$

For A_4 , it is clear, since $a_{1n} a_{n1} = 0$ the H. Wang preconditioner is invalid but by our new preconditioner we have the new results that are given in Table 4. Let,

$$A_5 = \begin{pmatrix} 1 & -0.2 & -0.2 & -0.1 & -0.25 & -0.4 \\ 0 & 1 & 0 & -1 & 0 & 0 \\ -0.3 & -0.5 & 1 & -0.05 & -0.25 & -0.1 \\ -0.25 & -0.1 & -0.55 & 1 & -0.3 & -0.1 \\ -0.2 & -0.15 & -0.3 & -0.05 & 1 & -0.5 \\ -0.3 & -0.25 & -0.25 & -0.1 & -0.3 & 1 \end{pmatrix}$$

For A_5 , the numerical results are given in Table 5.

5. Numerical Example

In this section we give the numerical examples to illustrate the results obtained in Sections 3 and 4. In all tables, we report the spectral radii of the corresponding iteration matrix. In these tables n represents the dimension of matrix and also, the meaning of notations J and GS are the Jacobi and Gauss-Seidel iterative methods and $M_i(r, t)$ is the vector (r, t) where r and t are obtained by Model i , $i=1, 3$ in [10], $M_{m_i}(r, t)$ is the vector (r, t) where r and t are obtained by Model i , $i=1, 2$. $\rho_1, \rho_3, \rho_{m_1}$ and ρ_{m_2} are the spectral radii of iteration matrices when the preconditioned to (1) obtained by Model1, Model3 in [10], Model1 and Model2, respectively. The numerical results in the following tables are computed using MATLAB 7.9. (See [10].) Let

$$A_1 = \begin{pmatrix} 1.00000 & -0.00580 & -0.19350 & -0.25471 & -0.03885 \\ -0.28424 & 1.00000 & -0.16748 & -0.21780 & -0.21577 \\ -0.24764 & -0.26973 & 1.00000 & -0.18723 & -0.08949 \\ -0.13880 & -0.01165 & -0.25120 & 1.00000 & -0.13236 \\ -0.25809 & -0.08162 & -0.13940 & -0.04890 & 1.00000 \end{pmatrix}$$

$$A_2 = \begin{pmatrix} 1.00000 & -0.23661 & -0.37369 & -0.25833 & -0.05480 \\ -0.13602 & 1.00000 & -0.10578 & -0.38675 & -0.32750 \\ -0.12569 & -0.01525 & 1.00000 & -0.26597 & -0.17207 \\ -0.14603 & -0.18344 & -0.34914 & 1.00000 & -0.35613 \\ -0.15730 & -0.34795 & -0.09515 & -0.00397 & 1.00000 \end{pmatrix}$$

Note that A_1 is a strictly diagonally dominant matrix, but A_2 is not. Since, for the A_1 and A_2 , the module of the off diagonal of elements are less than one so, we consider $\alpha = -\frac{1}{a_{rr}} > 1$ and $\beta = 0$, clearly $(\tilde{S}_{\alpha \beta r t})_{r,t} = 1$. The numerical results are given in Tables 1 and 2. (see [7].)

For A_3 , we report the spectral radii of the corresponding preconditioned iteration matrix that obtained by Model2. The numerical results are given in Table3.

Table 1. Comparison of the spectral radii of the Jacobi, method for Example, 5

	$M_1(r, t)$	ρ_1	$M_3(r, t)$	ρ_3	
A_1	(4, 5)	0.490685	(2, 1)	0.579796	
A_2	(2, 3)	0.769261	(4, 3)	0.751899	
	$M_{m_1}(r, t)$	ρ_{m_1}	$M_{m_2}(r, t)$	ρ_{m_2}	$\rho(J)$
A_1	(2, 3)	0.550251	(2, 1)	0.599796	0.629054
A_2	(4, 2)	0.709061	(4, 3)	0.751899	0.767901

Table 2. Comparison of the spectral radii of the Gauss-Seidel, method for Example, 5

	$M_1(r,t)$	ρ_1	$M_3(r,t)$	ρ_3	
A_1	(4,5)	0.364181	(2,1)	0.383960	
A_2	(2,3)	0.534910	(4,3)	0.646546	
	$M_{m_1}(r,t)$	ρ_{m_1}	$M_{m_2}(r,t)$	ρ_{m_2}	$\rho(GS)$
A_1	(2,1)	0.383960	(2,4)	0.333417	0.384956
A_2	(2,4)	0.574424	(2,4)	0.574424	0.684891

Table 3. Numerical results for Example, 5

	$n = 10$	$n = 20$	$n = 30$
(γ, ω)	(0.85, 0.9)	(0.7, 0.95)	(0.85, 0.95)
(α, β)	(100, -14.14286)	(50, -13.99999)	(200, -14.21428)
$M_{m_2}(r,t)$	(10, 1)	(20, 1)	(30, 1)
ρ_{m_2}	0.169754	0.172622	0.158450
$\rho(L_{\gamma,\omega})$	0.725002	0.738723	0.708978

Table 4. Numerical results for Example, 5

	(γ, ω)	(α, β)	$M_{m_2}(r,t)$	ρ_{m_2}	$\rho(L_{\gamma,\omega})$
$n = 10$	(0.85, 0.9)	(100, -14)	(1, 2)	0.31933	0.76464
$n = 20$	(0.7, 0.95)	(100, -14)	(1, 2)	0.34243	0.77516
$n = 30$	(0.85, 0.95)	(200, -14)	(1, 2)	0.30978	0.74675

Table 5. Numerical results for Example, 5

(γ, ω)	(α, β)	(r,t)	$\rho(L_{\gamma,\omega}^{r,t})$	$\rho(L_{\gamma,\omega})$
(0.85, 0.9)	(10, 0)	(1, 4)	1.30360	1.30301
(0.7, 0.95)	(5, 0)	(5, 3)	1.28053	1.27812
(0.85, 0.95)	(40, 0)	(6, 5)	1.32026	1.31985

6. Conclusion

This paper presents new preconditioned AOR iterative method that is valid even $a_{1n}a_{n1} = 0$, and from the above numerical experiments, we get that the results are in concord with Theorems in Section3. Also we introduced two models to construct a better $I + S$ type preconditioned AOR iterative method. The Model2 is independent of choosing α and β , but a natural problem is, how to choose the optimal parameters α and β . Further research is required.

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