LEFT-LOOKING APPROXIMATE INVERSE PRECONDITIONER IN BLOCK FORM

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ABSTRACT. In this paper we present a block version of left-looking AINV preconditioner. In the numerical tests, we compare the quality of the plain and block versions of this preconditioner.

Keywords: AINV preconditioner; GMRES method.

1. Introduction

Consider the linear system

$$Ax = b$$

where $A \in \mathbb{R}^{n \times n}$ is real, nonsymmetric and invertible matrix and $x, b \in \mathbb{R}^{n \times 1}$. The left-looking A-biconjugation algorithm can be used to factorize A^{-1} in the following form

$$A^{-1} = ZD^{-1}W^T$$
.

In this factorization Z and W are unit upper triangular matrices and D is a diagonal matrix [1]. If we apply dropping in this algorithm, then the left-looking AINV will be obtained. In [2], we have presented a block format of left-looking A-biconjugation algorithm. In this case, Z and W factors are agin unit upper triangular while D is a block diagonal matrix. The diagonal blocks of D are of order 1×1 or 2×2 . Applying the dropping strategy in this block algorithm will give us a block version of left-looking AINV preconditioner. In this paper, we will compare the quality of the block and plain left-looking AINV preconditioners at reducing the number of iterations of the GMRES [4] Krylov subspace method.

2. Algorithms of Plain and Block Left-looking AINV preconditioners

In this section, we have presented three algorithms. Algorithm 1 and 2 are used to compute the block version of left-looking AINV preconditioner. We call Algorithm 2 inside Algorithm 1 to construct a column of matrices Z and W.

2010 Mathematics Subject Classification. 65F10, 65F08.

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Algorithm 1 (A block format of left-looking AINV preconditioner)

Input: $A \in \mathbb{R}^{n \times n}$ a nonsymmetric matrix, $\tau_w, \tau_z \in (0,1)$ are the drop tolerance parameters for W and Z. Output: $A^{-1} \approx ZD^{-1}W^T$, Z and W are unit upper triangular and D is a block diagonal matrix.

```
 \begin{array}{l} 1. \ logic\_z = logic\_w = true \\ 2. \ status(i) = 0, \ 1 \leq i \leq n \\ 3. \ Z = [z_1^{(0)}, z_2^{(0)}, ..., z_n^{(0)}] = I_{n \times n}, W = [w_1^{(0)}, w_2^{(0)}, ..., w_n^{(0)}] = I_{n \times n}, D = 0 \in \mathbb{R}^{n \times n} \end{array} 
5. \mathcal{L} = \frac{1}{4}. i = 1
5. while 6. if 7. 8. el 9. 10. e
                   if logic_z then
                            call\ column-const(Z,\tau_{z},A,D,i,status)
                    else
                            logic\_z = true
                      end if
                     end if call column - const(Z, \tau_z, A, D, i+1, status) S_{ii}^{(i-1)} = e_i^T A z_i^{(i-1)}
 11.
 12.
                     \begin{aligned} & S_{ii} & - C_i & M_i \\ & \text{for } j = i+1 \text{ to } n \text{ do} \\ & S_{ji}^{(i-1)} = e_j^T A z_i^{(i-1)}, \quad S_{j,i+1}^{(i-1)} = e_j^T A z_{i+1}^{(i-1)} \end{aligned}
 13.
 14.
 15.
                       end for
                      \mathbf{if}\ logic\_w\ \mathbf{then}
17.
18.
19.
20.
21.
                              column-const(W, \tau_w, A^T, D^T, i, status)
                      _{
m else}
                     logic\_w = true end if
                    \begin{array}{l} \mathbf{end} \ \ \mathbf{if} \\ call \ column - const(W, \tau_w, A^T, D^T, i+1, status) \\ S_{ij}^{(i-1)} = (w_i^{(i-1)})^T A e_j, \quad j \geq i+1 \\ S_{i+1,j}^{(i-1)} = (w_{i+1}^{(i-1)})^T A e_j, \quad j \geq i+2 \\ v_i = max \{ \frac{1}{|s_{ij}^{(i-1)}|} \sum_{j=i+1}^n |S_{ii}^{(i-1)}|, \quad \frac{1}{|s_{ii}^{(i-1)}|} \sum_{j=i+1}^n |S_{ji}^{(i-1)}| \\ \end{array}
22.
23.
24.
                    \begin{split} w_i^1 &= \sum_{j=i+2}^n || \begin{bmatrix} S_{ii}^{(i-1)} & S_{i+1}^{(i-1)} \\ S_{i+1,i}^{(i-1)} & S_{i+1,i+1}^{(i+1)} \end{bmatrix}^{-1} \begin{pmatrix} S_{ij}^{(i-1)} \\ S_{i+1,j}^{(i-1)} \end{pmatrix} ||_{\infty} \\ w_i^2 &= \sum_{j=i+2}^n || \begin{pmatrix} S_{ij}^{(i-1)} & S_{i+1,i+1}^{(i-1)} \\ S_{i+1,j}^{(i-1)} & S_{i,i+1,j}^{(i-1)} \end{bmatrix}^{-1} \\ S_{i+1,i}^{(i-1)} & S_{i+1,i+1}^{(i-1)} \end{bmatrix}^{-1} ||_{\infty} \end{split}
25.
26.
                    w_i = max\{w_i^1, w_i^2\}

if v_i < w_i then

D_{ii} = S_{ii}^{(i-1)}
 28.
29.
                           z_{i+1}^{(i)} = z_{i+1}^{(i-1)} - (\frac{e_i^T A z_{(i+1)}^{(i-1)}}{D_{ii}}) z_i^{(i-1)}. \text{ For all } l \leq i \text{ apply dropping rule to } z_{l,i+1}^{(i)} \text{ if its absolute value is less than } \tau_z
30.
                           w_{i+1}^{(i)} = w_{i+1}^{(i-1)} - (\frac{(w_{i+1}^{(i-1)})^T A e_i}{D_{ii}}) w_i^{(i-1)}. \text{ For all } l \leq i \text{ apply dropping rule to } w_{l,i+1}^{(i)} \text{ if its absolute value is less than } \tau_w \\ logic_z = false, \quad logic_w = false \\ status(i) = 1 \\ i = i + 1 \\ 1 \\ \end{cases}
31.
32.
33.
34.
35.
                               i = i + 1
                            \begin{array}{l} D_{i:i+1,i:i+1} = \begin{bmatrix} S_{ii}^{(i-1)} & S_{ii+1}^{(i-1)} \\ S_{i+1}^{(i-1)} & S_{i+1i+1}^{(i-1)} \end{bmatrix} \\ z_{i+1}^{(i)} = z_{i+1}^{(i-1)}, & w_{i+1}^{(i)} = w_{i+1}^{(i-1)} \\ status(i) = 2 \\ i = i+2 \end{array}
36.
37.
 38.
30. status(i) = 2

39. i = i + 2

40. end if

41. end while

42. if status(n - 1) = 0 then
                    i = i + 2 end if
                 \begin{array}{l} \text{call } column-const(Z,\tau_z,A,D,n,status) \\ \text{call } column-const(W,\tau_w,A^T,D^T,n,status) \\ D_{n,n}=e_{n}^{T}Az_{n}^{(n-1)} \end{array} 
 43.
 44.
 45.
46. end if 47. if status(n-1) = 1 then
48. D_{n,n} = e_n^T A z_n^{(n-1)}
 49. end if
50. Return Z = [z_1^{(0)}, z_2^{(1)}, ..., z_n^{(n-1)}], W = [w_1^{(0)}, w_2^{(1)}, ..., w_n^{(n-1)}] and D
```

Algorithm 3 gives the plain left-looking AINV preconditioner. This algorithm was first introduced by Benzi and Tuma in reference [1].

Algorithm 2 (Column construction of a matrix)

```
Column. Const(Z, \tau_z, A, D, i, status)
Input: Z = [z_1^{(0)}, z_2^{(1)}, \cdots, z_{i-1}^{(i-2)}, z_i^{(0)}, \cdots, z_n^{(0)}] \in \mathbb{R}^{n \times n}, \tau_z \in (0, 1) is the drop tolerance for Z, A \in \mathbb{R}^{n \times n} a nonsymmetric matrix, D \in \mathbb{R}^{n \times n} a block diagonal matrix, i is an integer, status is an integer array
Output: updated Z
1. j = 1
2. while j \leq i - 1 do
3. k = j + status(j) - 1
4. if status(j) = 1 then
5. z_i^{(k)} = z_i^{(j-1)} - z_j^{(j-1)} \times \frac{1}{D_{jj}} \times A_{j,:} \times z_i^{(j-1)}
6. j = j + 1
7. else if status(j) = 2 then
8. z_i^{(k)} = z_i^{(j-1)} - [z_j^{(j-1)} z_{j+1}^{(j)}] \times [D(j:j+1,j:j+1)]^{-1} \times A_{j:j+1,:} \times z_i^{(j-1)}
9. j = j + 2
10. end if
11. Consider z_i^{(k)} = (z_{li}^{(k)}). For all l, apply dropping rule to z_{li}^{(k)} if its absolute value is less than \tau_z
12. end while
13. Return Z
```

Algorithm 3 (Left-looking AINV preconditioner)

```
Input: A \in \mathbb{R}^{n \times n} a nonsymmetric matrix, \tau_w, \tau_z \in (0,1) the drop tolerances for W and Z. Output: A^{-1} \approx ZD^{-1}W^T.

1. D = 0 \in \mathbb{R}^{n \times n}
2. for i = 1 to n do
3. w_i^{(0)} = e_i, z_i^{(0)} = e_i
4. for j = 1 to i - 1 do
5. w_i^{(j)} = w_i^{(j-1)} - (\frac{(w_i^{(j-1)})^T A e_j}{D_{jj}}) w_j^{(j-1)}, z_i^{(j)} = z_i^{(j-1)} - (\frac{e_j^T A z_i^{(j-1)}}{D_{jj}}) z_j^{(j-1)}
6. for all l \leq j apply a dropping rule to w_{li}^{(j)} and to z_{li}^{(j)} if their absolute values are less than \tau_w and \tau_z.
7. end for
8. D_{ii} = e_i^T A z_i^{(i-1)}
9. end for
10. Return Z = [z_1^{(0)}, z_2^{(1)}, \cdots, z_n^{(n-1)}], W = [w_1^{(0)}, w_2^{(1)}, \cdots, w_n^{(n-1)}] and D = diag(D_{ii})_{1 \leq i \leq n}.
```

3. Numerical tests

In this section, we have reported the results of numerical experiments. We have implemented 3 algorithms in Matlab. We have selected 4 matrices from [3]. Then, we constructed the artificial linear systems $A[1,\cdots,1]^T=b$. These systems have been solved by the GMRES(15) Krylov subspace method. The command GMRES in Matlab provides us this method. The matrix information and the convergence results of the GMRES(15) can be found in Table 1. In this table, n and nnz are the dimension and number of nonzero entries of the matrix. iter(1) and iter(2) are the number of external and internal iterations of GMRES(15), respectively. Time is the iteration time which is in seconds.

Table 1. matrix properties and results of GMRES(15)

Matrix	propert	ies	GMRES(15)				
name	n	nnz	iter(1)	iter(2)	Time		
sherman4	1104	3786	37	12	0.305		
orsirr-2	886	5970	397	9	1.629		
sherman1	1000	2375	132	15	0.559		
cdde1	961	4681	9	2	0.035		

In Table 2, we have set $\tau_z = \tau_w = 0.1$ and computed both the plain and the block left-looking AINV preconditioners. The notations LLAINV(0.1) and BLLAINV(0.1) refer to these two cases. Then, these two preconditioners have been used as the right preconditioner for linear systems. After that, the preconditioned systems have been solved by the GMRES(15) method. The results of these tests can be found in Table 2. In this table, ptime is the preconditioning time which is in seconds and density is defined as

$$density = \frac{nnz(Z) + nnz(W)}{nnz(A)},$$

where nnz(Z), nnz(W) and nnz(A) are the number of nonzero entries of matrices Z, W and A, respectively. In this table, iter(1) and iter(2) have the same definition as in Table 1 and Ttime is the summation of preconditioning time and the iteration time of the GMRES(15) method.

TABLE 2. properties of the preconditioners and results of GMRES(15) to solve the preconditioned systems

	LLAINV(0.1)+GMRES(15)				BLLAINV(0.1)+GMRES(15)					
matrix	ptime	density	iter(1)	iter(2)	Ttime	ptime	density	iter(1)	iter(2)	Ttime
sherman4	40.84	1.331	7	13	41.0025	5641.11	4.079	7	3	5641.44
orsirr-2	26.05	0.919	4	10	26.1109	3321.73	3.458	4	9	3321.79
sherman1	29.61	1.350	1	6	29.621	3589.79	1.551	1	6	3589.8
cdde1	34.41	1.558	20	14	34.7793	4550.61	15.341	9	1	4550.76

The results in Table 2 indicate that for matrices sherman4, or sirr-2 and cdde1, the block left-looking AINV preconditioner is more effective than the plain left-looking AINV at reducing the number of iterations of GMRES(15) method. For matrix sherman1, both preconditioners make the GMRES(15) method convergent in the same number of iterations. Comparing the preconditioning time of both preconditioners show that the block left-looking AINV needs more time to be constructed. By analyzing the number of iterations in Tables 1 and 2 one may come to conclusion that both preconditioners are effective tools at reducing the number of iterations of GMRES(15) method.

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