ONE NEW TYPE OF INTERLEAVED ITERATIVE ALGORITHM FOR H-MATRICES

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ABSTRACT. In the theory and the applications of Numerical Linear Algebra, the class of H-matrices is very important. In recent years, many appeared works have proposed iterative criterion for H-matrices. In this paper, we provide a new type of interleaved iterative algorithm, which is always convergent in finite steps for H-matrices and needs fewer iterations than those proposed in the related works, and a corresponding algorithm for general matrix, which eliminates the redundant computations when the given matrix is not an H-matrix. Finally, several numerical examples are presented to show the effectiveness of the proposed algorithms.

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1. Introduction

H-matrices play a vital role in both the theory and the applications of Numerical Linear Algebra. Many appeared works have proposed various criterions(algorithms) that identify whether a matrix to be solved is an H-matrix or not^[1-9]. At first, we give notations and definitions as follows:

In this paper, $C^{n\times n}(R^{n\times n})$ will be used to denote the set of all $n\times n$ complex(real) matrices. $N=\{1,2,\ldots,n\}$. Let $A=(a_{ij})\in C^{n\times n}$, and $R_i(A)=\sum_{j\neq i}|a_{ij}|\ ,\ i\in N, \qquad N_0(A)=\{\ i\mid |a_{ii}|=R_i(A)\ ,i\in N\},$

$$N_1(A) = \{i \mid |a_{ii}| > R_i(A), i \in N\}, N_2(A) = \{i \mid 0 < |a_{ii}| < R_i(A), i \in N\}.$$

If $|a_{ii}| > R_i(A)$, $\forall i \in N$, then A is called a strictly diagonally dominant matrix. And if there exists a positive diagonal matrix D such that AD is strictly diagonally dominant, then A is called a generalized diagonally dominant matrix

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(GDDM), we denote this by $A \in \widetilde{D}$. It is well known that A is a GDDM if and only if A is a nonsingular H-matrix.

Matrix A is called a reducible matrix, if there exists a subset $K: \phi \neq K \subset N$, satisfies

$$a_{ij} = 0$$
, for any $i \in K$, $j \in N \setminus K$.

If A is not a reducible matrix, we call A is an irreducible matrix.

Definition 1. We define the comparison matrix of A, $\mu(A) = (\alpha_{ij})$, by

$$\alpha_{ij} = \left\{ \begin{array}{ll} |a_{ii}|, & i = j, \\ -|a_{ij}|, & i \neq j. \end{array} \right.$$

If the eigenvalues of $\mu(A)$ have positive real parts, we call $\mu(A)$ an M-matrix. We say that A is an H-matrix if and only if $\mu(A)$ is an M-matrix.

It is obvious that, as defined above, every H-matrix is nonsingular.

Definition 2. Let A be an irreducible matrix, if for all $i \in N$,

$$|a_{ii}| \ge R_i(A),\tag{1}$$

and there exists at least one strict inequality in (1), then A is called an irreducible diagonally dominant matrix.

Lemma 1[10]. Let A is an irreducible matrix. If for all $i \in N$,

$$|a_{ii}| \ge R_i(A), \tag{2}$$

and there exists at least one strict inequality in (2), then A is an H-matrix.

We know that A is an H-matrix if $N_0(A) \bigcup N_2(A) = \emptyset$, and A is not an H-matrix if $N_1(A) = \emptyset$. So in this paper, set $N_0(A) \bigcup N_2(A) \neq \emptyset$, and $N_1(A) \neq \emptyset$.

Because it is difficult to find a proper D for an H-matrix such that AD is strictly diagonally dominant, an efficient iterative algorithm is required. Recently, Li $et\ al.$ in [2] have proposed a non-parameter iterative method for generalized diagonally dominant matrices, and T. Kohno $et\ al.$ in [3] gave an algorithmic procedure to eliminate redundant computations of iterations when A is not an H-matrix. Liu and He in [1] provide two improved algorithm by means of interleaved iteration, which need fewer iterations than that of Li $et\ al.$ in [1] and T. Kohno $et\ al.$ in [3], and other methods show in [4-9].

In this paper, we provide an interleaved iterative algorithms for H-matrices, which is always convergent in finite steps and needs fewer iterations than those in [1-3], and then give a corresponding algorithm for general matrix to eliminate redundant iterations when the given matrix is not an H-matrix. Finally, several numerical examples are presented to show the effectiveness of the proposed algorithms.

2. The algorithms

First, set $A=(a_{ij})\in C^{n\times n}$, satisfying $a_{ii}\neq 0$, for all $i\in N$, we will use the notations as follows:

$$h = \max_{i \in N_1(A)} \left(\frac{\gamma_i + \beta_i}{P_i - \sum\limits_{t \in N_1(A), t \neq i} |a_{it}| \frac{P_t}{|a_{tt}|}} \right).$$

Algorithm A(L. Li et al. in [2]). Suppose $A = (a_{ij}) \in C^{n \times n}$, $a_{ii} \neq 0$, is an irreducible matrix. Let $N_1(A) \neq \phi$.

(A)
$$N_1(A) = 0$$
, $N_2(A) = 0$. For $i = 1, 2, ..., n$, do {

(A1) Compute $R_i(A) = \sum_{i \neq i} |a_{ij}|$,

(A2) If
$$|a_{ii}| > R_i(A)$$
, then $\{ N_1(A) = 1, d_i = \frac{R_i(A)}{|a_{ii}|},$

$$a_{ji} = a_{ji} * d_i, \qquad j = 1, 2, \dots, n$$

else if
$$|a_{ii}| < R_i(A)$$
, then $N_2(A) = 1$,

- (B) If $N_1(A) = 0$, then print 'A is not a GDDM', go to (C). else if $N_2(A) = 0$, then print 'A is a GDDM', go to (C). else return to (A).
- (C) End.

Algorithm A'(Liu and He in [1]). Input: a given irreducible matrix $A = (a_{ij}) \in$ $C^{n\times n}$.

Output: $D = D^{(1)}D^{(2)} \cdots D^{(m)} \in \mathcal{D}_A$ if A is an H-matrix.

- 1. if $N_1(A) = \phi$ or $a_{ii} = 0$ for some $i \in N$, 'A is not an H-matrix', stop; otherwise,
- 2. set m = 1, $A^{(0)} = A$, $D^{(0)} = I$, 3. compute $A^{(m)} = A^{(m-1)}D^{(m-1)} = (a_{ij}^{(m)})$,
- 4. if $N_1(A^{(m)}) = \phi$, 'A is not an H-matrix', stop; if $N_1(A^{(m)}) \cup N_0(A^{(m)}) = N$, 'A is an

H-matrix', stop; otherwise,

5. compute
$$\alpha_{i}^{(m)}$$
, $\beta_{i}^{(m)}$, $\gamma_{i}^{(m)}$, $i \in N$,
6. set $r_{2} = \max_{i \in N_{1}(A^{(m)})} \frac{\beta_{i}^{(m)} + \gamma_{i}^{(m)}}{|a_{ii}^{(m)}| - a_{i}^{(m)}}$,

7. set $d = (d_i)$, where

$$\text{If m is an odd number,then } d_i = \begin{cases} \frac{R_i(A^{(m)})}{|a_{ii}^{(m)}|}, & \text{if } i \in N_1(A^{(m)}), \\ 1, & \text{if } i \in N_0(A^{(m)}) \bigcup N_2(A^{(m)}) \,. \end{cases}$$

 $\text{If } m \text{ is an even number, then } d_i = \begin{cases} r_2, & \text{if } i \in N_1(A^{(m)}), \\ 1, & \text{if } i \in N_0(A^{(m)}) \bigcup N_2(A^{(m)}). \end{cases}$

8. set $D^{(m)} = diag(d), m = m + 1$, go to step 3.

Next, we provide a new improved interleaved iteration algorithm.

Algorithm I. Input: a given irreducible matrix $A = (a_{ij}) \in C^{n \times n}$.

Output: $D = D^{(1)}D^{(2)} \cdots D^{(m)} \in \mathcal{D}_A$ if A is an H-matrix.

- 1. if $N_1(A) = \phi$ or $a_{ii} = 0$ for some $i \in N$, 'A is not an H-matrix', stop;
- 2. set m = 1, $A^{(0)} = A$, $D^{(0)} = I$.
- 3. compute $A^{(m)} = A^{(m-1)}D^{(m-1)} = (a_{i,i}^{(m)})$,
- 4. if $N_1(A^{(m)}) = \phi$, 'A is not an H-matrix', stop; if $N_1(A^{(m)}) \bigcup N_0(A^{(m)}) = N$, 'A is an

H-matrix', stop; otherwise,

- 5. compute $\alpha_{i}^{(m)}$, $\beta_{i}^{(m)}$, $\gamma_{i}^{(m)}$, $\forall i \in N$,
 6. compute $r_{0}^{(m)}$, $P_{i}^{(m)}$, $h^{(m)}$, $\forall i \in N_{1}(A^{(m)})$,
 7. set $r_{i} = \frac{h^{(m)}P_{i}^{(m)}}{|a_{i}^{(m)}|}$,
- 8. set $d = (d_i)$, where

 $\text{If m is an odd number, then } d_i = \begin{cases} \frac{R_i(A^{(m)})}{|a_{ii}^{(m)}|}, & \text{if } i \in N_1(A^{(m)}), \\ 1, & \text{if } i \in N_0(A^{(m)}) \bigcup N_2(A^{(m)}). \end{cases}$

If m is an even number, then $d_i = \begin{cases} r_i, & \text{if } i \in N_1(A^{(m)}), \\ 1, & \text{if } i \in N_0(A^{(m)}) \bigcup N_2(A^{(m)}). \end{cases}$

9. set $D^{(m)} = diag(d), m = m + 1$, go to step 3.

Remark 1. In Algorithm I, A is an irreducible matrix, so for all $i \in N_1(A^{(m)})$, we have

$$0 < r_0^{(m)} < 1, \ 0 < \frac{P_i^{(m)}}{|a_{ii}^{(m)}|} < 1,$$

and

$$\begin{split} r_0^{(m)} \geq \frac{\gamma_i^{(m)} + \beta_i^{(m)}}{\mid a_{ii}^{(m)} \mid -\alpha_i^{(m)}} \,, \\ r_0^{(m)} \mid a_{ii}^{(m)} \mid \geq \gamma_i^{(m)} + r_0^{(m)} \alpha_i^{(m)} + \beta_i^{(m)} = P_i^{(m)}, \quad r_0^{(m)} \geq \frac{P_i^{(m)}}{\mid a_{ii}^{(m)} \mid} \,, \end{split}$$

and

$$\frac{\gamma_{i}^{(m)} + \beta_{i}^{(m)}}{P_{i}^{(m)} - \sum\limits_{t \in N_{1}(A^{(m)}), t \neq i} |a_{it}^{(m)}| \frac{P_{t}^{(m)}}{|a_{tt}^{(m)}|}} = \frac{P_{i}^{(m)} - r_{0}^{(m)} \alpha_{i}^{(m)}}{P_{i}^{(m)} - \sum\limits_{t \in N_{1}(A^{(m)}), t \neq i} |a_{it}^{(m)}| \frac{P_{t}^{(m)}}{|a_{it}^{(m)}|}} \\ \leq \frac{P_{i}^{(m)} - \sum\limits_{t \in N_{1}(A^{(m)}), t \neq i} |a_{it}^{(m)}| \frac{P_{t}^{(m)}}{|a_{it}^{(m)}|}}{P_{i}^{(m)} - \sum\limits_{t \in N_{1}(A^{(m)}), t \neq i} |a_{it}^{(m)}| \frac{P_{t}^{(m)}}{|a_{it}^{(m)}|}} = 1,$$

then

$$0 < h^{(m)} \le 1,$$

$$0 < \frac{h^{(m)} P_i^{(m)}}{|a_{ii}^{(m)}|} = r_i \le \frac{P_i^{(m)}}{|a_{ii}^{(m)}|} \le r_0^{(m)} = r_2 < 1, \ \forall i \in N_1(A^{(m)}).$$

Therefore we have that this algorithm needs fewer number of iterations than Algorithm A and A'. The theoretical analysis of Algorithm I as a characterization of H-matrices is presented by the following theorem:

Theorem 1. $A = (a_{ij}) \in \mathbb{C}^{n \times n}$ is an irreducible H-matrix if and only if Algorithm I stops after a finite number of iterations by producing a strictly diagonally dominant matrix.

Proof. Sufficiency: Suppose that Algorithm I stops after m iterations. That means, we have obtained a strictly diagonally dominant matrix $A^{(m)} = A^{(0)}D^{(1)}$ $D^{(2)}\cdots D^{(m-1)} = AD$, where $D = D^{(0)}D^{(1)}\cdots D^{(m-1)}$ is a positive diagonal matrix. Thus, A is an irreducible H-matrix.

Necessity: Let A be an irreducible H-matrix. For notational convenience, we assume A is a nonnegative matrix. By using way of contradiction, suppose that Algorithm I doesn't stop after a finite number of iterations. From Algorithm I, we have $A^{(m)} = A^{(1)}D^{(1)}D^{(2)}\cdots D^{(m-1)} = AD$, where $D = D^{(1)}D^{(2)}\cdots D^{(m-1)}$ is a positive diagonal matrix, then it is obvious that

$$A = A^{(1)} \ge \cdots \ge A^{(m)} \ge \cdots \ge 0.$$

The infinite matrix sequence $\{A^{(m)}\}$ is bounded and monotone decreasing, then we have

$$\lim_{m\to\infty}A^{(m)}=B\geq 0\,,$$

where B = AF, $F = D^{(1)}D^{(2)}\cdots D^{(m)}\cdots$ is a positive diagonal matrix. Next, we want to prove

$$\lim_{m \to \infty} N_1(A^{(m)}) = N_1(B) = \phi.$$

By using way of contradiction again, we assume $\lim_{m\to\infty} N_1(A^{(m)}) \neq \phi$, then $1-r_i>0$, $\forall i\in N_1(A^{(m)})$ and there exist some i and ε_1 , ε_2 such that

$$a_{ii}^{(m)} - R_i(A^{(m)}) > \varepsilon_1, \quad a_{ii}^{(m)}(1 - r_i) > \varepsilon_2, \quad m = 1, 2, \dots$$

We set $\varepsilon_0 = \min\{\varepsilon_1, \varepsilon_2\}.$

When m is an odd number, from Algorithm I, we have

$$0 < a_{ii}^{(m+1)} = a_{ii}^{(m)} \frac{R_i(A^{(m)})}{a_{ii}^{(m)}}$$
$$= a_{ii}^{(m)} - \left(a_{ii}^{(m)} - R_i(A^{(m)})\right)$$
$$< a_{ii}^{(m)} - \varepsilon_0.$$

When m is an even number, from Algorithm I, we have

$$0 < a_{ii}^{(m+1)} = a_{ii}^{(m)} r_i$$
 $< a_{ii}^{(m)} - \varepsilon_2$
 $< a_{ii}^{(m)} - \varepsilon_0$

Note that ε_0 is positive and therefore

$$a_{ii}^{(0)} = a_{ii}^{(1)} > a_{ii}^{(2)} + \varepsilon_0 > \dots > a_{ii}^{(m)} + (m-1)\varepsilon_0.$$

Let $m \to \infty$. Then $a_{ii}^{(0)} \to \infty$, we obtain a contradiction. Thus,

$$\lim_{m\to\infty} N_1(A^{(m)}) = N_1(B) = \phi.$$

That means B is not an H-matrix. On the other hand there exists a positive diagonal matrix E such that $AE = B(F^{-1}E)$ is strictly diagonally dominant. We know that $F^{-1}E$ is still a positive diagonal matrix, so B is an H-matrix. Then we obtain another contradiction, completing the proof of this theorem.

The drawback of Algorithms I is that when A is not an H-matrix, it requires a large number of iterations. Kohno $et\ al.$ in [3] proposed a new algorithmic procedure to conquer this drawback, and Liu $et\ al.$ in [1] have improved it.

Algorithm B(T. Kohno et al. in [3]). Input: a given matrix $A = (a_{ij}) \in C^{n \times n}$. Output: $D = D^{(1)}D^{(2)}\cdots D^{(m)} \in \mathcal{D}_A$ if A is an H-matrix.

- 1. if $N_1(A) = \phi$ or $a_{ii} = 0$ for some $i \in N$, 'A is not an H-matrix', stop; otherwise,
- 2. set m = 1, $A^{(0)} = A$, $D^{(0)} = I$,
- 3. compute $A^{(m)} = A^{(m-1)}D^{(m-1)} = (a_{ij}^{(m)})$,
- 4. compute

$$d_i^{(m)} = rac{\sum_{j=1}^n |a_{ij}^{(m)}|}{|a_{ii}^{(m)}|}, \ \ i \in N.$$

5. if $d_i^{(m)} < 2$ for all i, 'A is an H-matrix', stop; if $d_i^{(m)} \geq 2$ for all i, 'A is not an H-matrix', stop; otherwise, 6. set $D^{(m)} = diag(d_i^{(m)}), m = m+1$, go to step 3.

Algorithm B' (Liu and He in [1]). Input: a given irreducible matrix $A = (a_{ij}) \in C^{n \times n}$.

Output: $D = D^{(1)}D^{(2)} \cdots D^{(m)} \in \mathcal{D}_A$ if A is an H-matrix.

1. if $N_1(A) = \phi$ or $a_{ii} = 0$ for some $i \in N$, 'A is not an H-matrix', stop; if $N_2(A) = \phi$, 'A

is an H-matrix', stop; otherwise,

2. set
$$m = 1$$
, $A^{(0)} = A$, $D^{(0)} = I$,

3. compute
$$A^{(m)} = A^{(m-1)}D^{(m-1)} = (a_{ij}^{(m)})$$
,

4. compute
$$\alpha_i^{(m)}$$
, $\beta_i^{(m)}$, $\gamma_i^{(m)}$, $i \in N$,

5. set
$$r_1 = \min_{i \in N_0(A^{(m)}) \cup N_1(A^{(m)})} \frac{\beta_i^{(m)}}{|a_{ii}^{(m)}| - \alpha_i^{(m)} - \gamma_i^{(m)}}$$

5. set $r_1 = \min_{i \in N_0(A^{(m)}) \cup N_1(A^{(m)})} \frac{\beta_i^{(m)}}{|a_{ii}^{(m)}| - \alpha_i^{(m)} - \gamma_i^{(m)}}$, 6. if $|a_{ii}^{(m)}| \le r_1 \alpha_i^{(m)} + \beta_i^{(m)} + r_1 \gamma_i^{(m)}$ for all $i \in N_2(A^{(m)})$, 'A is not an Hmatrix', stop;

otherwise,

$$7. \text{ set } r_2 = \max_{i \in N_1(A^{(m)})} \frac{\beta_i^{(m)} + \gamma_i^{(m)}}{\mid a_{ii}^{(m)} \mid -\alpha_i^{(m)}} \,,$$

8. if
$$N_0(A^{(m)}) \bigcup N_1(A^{(m)}) = N$$
 or $|a_{ii}^{(m)}| > r_2 \alpha_i^{(m)} + \beta_i^{(m)} + \gamma_i^{(m)}$ for all $i \in N_0(A^{(m)}) \bigcup$

 $N_2(A^{(m)})$, 'A is an H-matrix', stop; otherwise,

9. set $d = (d_i)$, where

$$\text{If m is an odd number, then } d_i = \begin{cases} \frac{R_i(A^{(m)})}{|a_{ii}^{(m)}|}, & \text{if $i \in N_1(A^{(m)})$,} \\ 1, & \text{if $i \in N_0(A^{(m)}) \bigcup N_2(A^{(m)})$.} \end{cases}$$

$$\text{If}\quad m \text{ is an even number,}\quad \text{then}\quad d_i = \begin{cases} r_2\,, & \text{if}\quad i \in N_1(A^{(m)})\,,\\ 1\,, & \text{if}\quad i \in N_0(A^{(m)}) \bigcup N_2(A^{(m)})\,. \end{cases}$$

10. set
$$D^{(m)} = diag(d), m = m + 1$$
, go to step 3.

Next, we give a new improved algorithm for general irreducible matrices on the basis of Algorithm B and B'.

Algorithm II. Input: a given irreducible matrix $A = (a_{ij}) \in C^{n \times n}$.

Output: $D = D^{(1)}D^{(2)} \cdots D^{(m)} \in \mathcal{D}_A$ if A is an H-matrix.

1. if $N_1(A) = \phi$ or $a_{ii} = 0$ for some $i \in N$, 'A is not an H-matrix', stop; if $N_2(A) = \phi, 'A$

is an H-matrix', stop; otherwise,

2. set
$$m = 1$$
, $A^{(0)} = A$, $D^{(0)} = I$,

2. set
$$m = 1$$
, $A^{(0)} = A$, $D^{(0)} = I$,
3. compute $A^{(m)} = A^{(m-1)}D^{(m-1)} = (a_{ij}^{(m)})$,

4. compute
$$\alpha_i^{(m)}$$
, $\beta_i^{(m)}$, $\gamma_i^{(m)}$, $i \in N$,

5. compute
$$r_0^{(m)}$$
, $P_i^{(m)}$, $h^{(m)}$, $\forall i \in N_1(A^{(m)})$,

$$\begin{aligned} &\text{4. compute } & R & = R & = -\left(a_{ij}^{(m)}\right), \\ &\text{4. compute } & \alpha_i^{(m)}, \ \beta_i^{(m)}, \ \gamma_i^{(m)}, \ i \in N, \\ &\text{5. compute } & r_0^{(m)}, \ P_i^{(m)}, \ h^{(m)}, \ \forall i \in N_1(A^{(m)}), \\ &\text{6. set } & r_1' = \min_{i \in N_0(A^{(m)}) \cup N_1(A^{(m)})} \frac{\beta_i^{(m)}}{|a_{ii}^{(m)}| - \sum\limits_{t \in N_1(A^{(m)}), t \neq i} |a_{it}^{(m)}| \frac{P_t^{(m)}}{|a_{it}^{(m)}|} - \gamma_i^{(m)}}, \end{aligned}$$

7. if $|a_{ii}^{(m)}| \leq r_1' \alpha_i^{(m)} + \beta_i^{(m)} + r_1' \gamma_i^{(m)}$ for all $i \in N_2(A^{(m)})$, 'A is not an Hmatrix', stop;

otherwise,
8. set
$$r_i = \frac{h^{(m)}P_i^{(m)}}{|a_{ii}^{(m)}|}$$
,

9. if
$$N_0(A^{(m)}) \bigcup N_1(A^{(m)}) = N$$
 or $|a_{ii}^{(m)}| > \sum_{t \in N_1(A^{(m)}), t \neq i} |a_{it}^{(m)}| \frac{h^{(m)} P_t^{(m)}}{|a_{it}^{(m)}|} +$

 $\beta_i^{(m)} + \gamma_i^{(m)} \text{ for all } i \in N_0(A^{(m)}) \bigcup N_2(A^{(m)}), \text{ `A is an H-matrix', stop; otherwise,}$ 10. set $d = (d_i)$, where

$$\text{If m is an odd number, then } d_i = \begin{cases} \frac{R_i(A^{(m)})}{|a_{ii}^{(m)}|}\,, & \text{if } i \in N_1(A^{(m)})\,, \\ 1\,, & \text{if } i \in N_0(A^{(m)}) \bigcup N_2(A^{(m)})\,. \end{cases}$$

 $\text{If} \quad m \text{ is an even number,} \quad \text{then} \quad d_i = \begin{cases} r_i \,, & \text{if} \quad i \in N_1(A^{(m)}) \,, \\ 1 \,, & \text{if} \quad i \in N_0(A^{(m)}) \bigcup N_2(A^{(m)}) \,. \end{cases}$

11. set $D^{(m)} = diag(d), m = m + 1$, go to step 3.

We prove the following theorem for Algorithm II.

Theorem 2. Let $A = (a_{ij}) \in \mathbb{C}^{n \times n}$ be an irreducible matrix, if Algorithm II

$$(1) \ \ \textit{When} \ |\ a_{ii}^{(k)}| \leq r_1' \alpha_i^{(k)} + \beta_i^{(k)} + r_1' \gamma_i^{(k)}, \ \textit{where} \ r_1' = \\ \min_{i \in N_0(\mathbf{A}^{(k)}) \cup N_1(\mathbf{A}^{(k)})} \frac{\beta_i^{(k)}}{|a_{ii}^{(k)}| - \sum\limits_{t \in N_1(\mathbf{A}^{(k)}) \mid r_i(t)} |a_{it}^{(k)}| \frac{P_i^{(k)}}{|a_{it}^{(k)}|} - \gamma_i^{(k)}}, \ \textit{then A is not an H-matrix};$$

(2) When
$$N_0(\mathbf{A}^{(k)}) \bigcup N_1(A^{(k)}) = N$$
 or $|a_{ii}^{(k)}| > \sum_{t \in N_1(A^{(k)}), t \neq i} r_t |a_{it}^{(k)}| + \beta_i^{(k)} + \sum_{t \in N_1(A^{(k)}), t \neq i} r_t |a_{it}^{(k)}| + \beta_i^{(k)} + \sum_{t \in N_1(A^{(k)}), t \neq i} r_t |a_{it}^{(k)}| + \beta_i^{(k)} + \sum_{t \in N_1(A^{(k)}), t \neq i} r_t |a_{it}^{(k)}| + \beta_i^{(k)} + \sum_{t \in N_1(A^{(k)}), t \neq i} r_t |a_{it}^{(k)}| + \beta_i^{(k)} + \sum_{t \in N_1(A^{(k)}), t \neq i} r_t |a_{it}^{(k)}| + \beta_i^{(k)} + \sum_{t \in N_1(A^{(k)}), t \neq i} r_t |a_{it}^{(k)}| + \beta_i^{(k)} + \sum_{t \in N_1(A^{(k)}), t \neq i} r_t |a_{it}^{(k)}| + \beta_i^{(k)} + \sum_{t \in N_1(A^{(k)}), t \neq i} r_t |a_{it}^{(k)}| + \beta_i^{(k)} + \sum_{t \in N_1(A^{(k)}), t \neq i} r_t |a_{it}^{(k)}| + \beta_i^{(k)} + \sum_{t \in N_1(A^{(k)}), t \neq i} r_t |a_{it}^{(k)}| + \beta_i^{(k)} + \sum_{t \in N_1(A^{(k)}), t \neq i} r_t |a_{it}^{(k)}| + \beta_i^{(k)} + \sum_{t \in N_1(A^{(k)}), t \neq i} r_t |a_{it}^{(k)}| + \beta_i^{(k)} + \sum_{t \in N_1(A^{(k)}), t \neq i} r_t |a_{it}^{(k)}| + \beta_i^{(k)} + \sum_{t \in N_1(A^{(k)}), t \neq i} r_t |a_{it}^{(k)}| + \beta_i^{(k)} + \sum_{t \in N_1(A^{(k)}), t \neq i} r_t |a_{it}^{(k)}| + \beta_i^{(k)} + \sum_{t \in N_1(A^{(k)}), t \neq i} r_t |a_{it}^{(k)}| + \beta_i^{(k)} + \sum_{t \in N_1(A^{(k)}), t \neq i} r_t |a_{it}^{(k)}| + \beta_i^{(k)} + \sum_{t \in N_1(A^{(k)}), t \neq i} r_t |a_{it}^{(k)}| + \beta_i^{(k)} + \sum_{t \in N_1(A^{(k)}), t \neq i} r_t |a_{it}^{(k)}| + \beta_i^{(k)} + \sum_{t \in N_1(A^{(k)}), t \neq i} r_t |a_{it}^{(k)}| + \beta_i^{(k)} + \sum_{t \in N_1(A^{(k)}), t \neq i} r_t |a_{it}^{(k)}| + \beta_i^{(k)} + \sum_{t \in N_1(A^{(k)}), t \neq i} r_t |a_{it}^{(k)}| + \beta_i^{(k)} + \sum_{t \in N_1(A^{(k)}), t \neq i} r_t |a_{it}^{(k)}| + \beta_i^{(k)} + \sum_{t \in N_1(A^{(k)}), t \neq i} r_t |a_{it}^{(k)}| + \beta_i^{(k)} + \sum_{t \in N_1(A^{(k)}), t \neq i} r_t |a_{it}^{(k)}| + \beta_i^{(k)} + \sum_{t \in N_1(A^{(k)}), t \neq i} r_t |a_{it}^{(k)}| + \beta_i^{(k)} + \sum_{t \in N_1(A^{(k)}), t \neq i} r_t |a_{it}^{(k)}| + \beta_i^{(k)} + \sum_{t \in N_1(A^{(k)}), t \neq i} r_t |a_{it}^{(k)}| + \beta_i^{(k)} + \sum_{t \in N_1(A^{(k)}), t \neq i} r_t |a_{it}^{(k)}| + \beta_i^{(k)} + \sum_{t \in N_1(A^{(k)}), t \neq i} r_t |a_{it}^{(k)}| + \sum_{t \in N_1(A^{(k)}), t \neq i} r_t |a_{it}^{(k)}| + \sum_{t \in N_1(A^{(k)}), t \neq i} r_t |a_{it}^{(k)}| + \sum$

$$\gamma_i^{(k)} \text{ for all } i \in N_0(A^{(k)}) \bigcup N_2(A^{(k)}), \text{ where } r_i = \frac{h^{(k)}P_i^{(k)}}{|a_{ii}^{(k)}|}, \text{ then } A \text{ is an H-matrix.}$$

Proof. For $\forall i \in N_1(A^{(m)})$, when m is an odd number, from Algorithm II, as $\frac{R_i(A^{(m)})}{|a^{(m)}|} < 1$, we have

$$\begin{aligned} |a_{ii}^{(m+1)}| - R_i(A^{(m+1)}) \\ &= |a_{ii}^{(m)}| \frac{R_i(A^{(m)})}{|a_{ii}^{(m)}|} - \sum_{i \in N_1(A^{(m)})} |a_{ij}^{(m)}| \frac{R_j(A^{(m)})}{|a_{jj}^{(m)}|} - \beta_i^{(m)} - \gamma_i^{(m)} \\ &\geq R_i(A^{(m)}) - \alpha_i^{(m)} - \beta_i^{(m)} - \gamma_i^{(m)} = 0. \end{aligned}$$

When m is an even number, from Algorithm II, we have

$$|a_{ii}^{(m+1)}| - R_i(A^{(m+1)})$$

$$= r_i|a_{ii}^{(m)}| - \sum_{t \in N_1(A^{(m)}), t \neq i} r_t|a_{it}^{(m)}| - \beta_i^{(m)} - \gamma_i^{(m)}$$

$$= h^{(m)} \left(P_i^{(m)} - \sum_{t \in N_1(A^{(m)}), t \neq i} |a_{it}^{(m)}| \frac{P_t^{(m)}}{|a_{tt}^{(m)}|} \right) - \beta_i^{(m)} - \gamma_i^{(m)}$$

$$\geq \frac{\beta_i^{(m)} + \gamma_i^{(m)}}{P_i^{(m)} - \sum_{t \in N_1(A^{(m)}), t \neq i} |a_{it}^{(m)}| \frac{P_t^{(m)}}{|a_{tt}^{(m)}|}} \left(P_i^{(m)} - \sum_{t \in N_1(A^{(m)}), t \neq i} |a_{it}^{(m)}| \frac{P_t^{(m)}}{|a_{tt}^{(m)}|} \right)$$

$$- \beta_i^{(m)} - \gamma_i^{(m)} = (\beta_i^{(m)} + \gamma_i^{(m)}) - \beta_i^{(m)} - \gamma_i^{(m)} = 0 .$$

Thus $(N_0(A^{(1)}) \bigcup N_1(A^{(1)})) \subseteq (N_0(A^{(2)}) \bigcup N_1(A^{(2)})) \subseteq \cdots \subseteq (N_0(A^{(k)}) \bigcup N_1(A^{(k)}))$. This means that multiplication with $D^{(m-1)}$ from the right doesn't change the diagonally dominant rows of $A^{(m-1)}$. Then,

(1) First we denote $\widetilde{N}_0(A) = \{i \in N_1(A) \mid \beta_i = 0\}, \ \xi_i = \sum_{j \in \widetilde{N}_0, \neq i} |a_{ij}|, \ \text{and if } \widetilde{N}_0(A) = \{i\} \text{ or } \widetilde{N}_0(A) = \phi, \text{ we set } \xi_i = 0.$

If $N_1(A^{(k)}) = \phi$, then $r'_1 = 1$. Furthermore $|a_{ii}^{(k)}| \leq \beta_i^{(k)} + \gamma_i^{(k)} = R_i(A^{(k)})$ for all $i \in N_2(A^{(k)})$, it is obvious that A is not an H-matrix, then we always assume $N_1(A^{(k)}) \neq \phi$ in the following.

When $N_1(A^{(k)}) \neq \phi$ and $\widetilde{N}_0(A^{(k)}) = \phi$, then $r_1' > 0$. We construct a positive diagonal matrix $\widetilde{D} = \operatorname{diag}\{\widetilde{d}_i \mid \widetilde{d}_i = r_1', i \in N_0(A^{(k)}) \bigcup N_1(A^{(k)}); \widetilde{d}_i = 1, i \in N_2(A^{(k)})\}$, and write $\widetilde{A} = A^{(k)} \widetilde{D} = (\widetilde{a}_{ij})$.

For
$$i \in N_0(A^{(k)}) \bigcup N_1(A^{(k)})$$
, as $\frac{P_i^{(k)}}{|a^{(k)}|} < 1, i \in N_1(A^{(k)})$, we have

$$\begin{split} &|\widetilde{a}_{ii}| - \widetilde{\alpha} - \widetilde{\beta} - \widetilde{\gamma} \\ &= r_1' |a_{ii}^{(k)}| - r_1' \alpha_i^{(k)} - \beta_i^{(k)} - r_1' \gamma_i^{(k)} \\ &= r_1' (|a_{ii}^{(k)}| - \alpha_i^{(k)} - \gamma_i^{(k)}) - \beta_i^{(k)} \\ &\leq \frac{\beta_i^{(k)}}{|a_{ii}^{(k)}| - \sum\limits_{t \in N_1(A^{(k)}), t \neq i} |a_{it}^{(k)}| \frac{P_t^{(k)}}{|a_{it}^{(k)}|} - \gamma_i^{(k)}} (|a_{ii}^{(k)}| - \alpha_i^{(k)} - \gamma_i^{(k)}) - \beta_i^{(k)} \\ &< \frac{\beta_i^{(k)}}{|a_{ii}^{(k)}| - \sum\limits_{t \in N_1(A^{(k)}), t \neq i} |a_{it}^{(k)}| \frac{P_t^{(k)}}{|a_{tt}^{(k)}|} - \gamma_i^{(k)}} (|a_{ii}^{(k)}| \\ &- \sum\limits_{t \in N_1(A^{(k)}), t \neq i} |a_{it}^{(k)}| \frac{P_t^{(k)}}{|a_{tt}^{(k)}|} - \gamma_i^{(k)}) - \beta_i^{(k)} = \beta_i^{(k)} - \beta_i^{(k)} = 0 \,. \end{split}$$

For $i \in N_2(A^{(k)})$, we have

$$|\widetilde{a}_{ii}| - \widetilde{\alpha} - \widetilde{\beta} - \widetilde{\gamma} = |a_{ii}^{(k)}| - r_1' \alpha_i^{(k)} - \beta_i^{(k)} - r_1' \gamma_i^{(k)} \le 0.$$

So \widetilde{A} has no diagonally dominant row. From Algorithm II, we obtain $\widetilde{A} = A^{(k)}\widetilde{D} = AD^{(1)}D^{(2)}\cdots D^{(k-1)}\widetilde{D}$, where $D^{(1)}D^{(2)}\cdots D^{(k-1)}\widetilde{D}$ is a positive diagonal matrix, thus A is not an H-matrix.

When $N_1(A^{(k)}) \neq \phi$ and $\widetilde{N}_0(A^{(k)}) \neq \phi$, then $r'_1 = 0$. Furthermore,

$$|a_{ii}^{(k)}| \le r_1' \alpha_i^{(k)} + \beta_i^{(k)} + r_1' \gamma_i^{(k)} = \beta_i^{(k)}, \quad \forall i \in N_2(A^{(k)}),$$

thus for any positive number d, we have

$$d | a_{ii}^{(k)} | \le d \beta_i^{(k)}, \quad \forall i \in N_2(A^{(k)}).$$

Notice that $\beta_i^{(k)} \neq 0$, $i \in (N_0(A^{(k)}) \bigcup N_1(A^{(k)})) \setminus \widetilde{N}_0(A^{(k)})$, we construct a positive diagonal matrix $\widehat{D} = diag\{\widehat{d}_i \mid \widehat{d}_i = c, i \in (N_0(A^{(k)}) \bigcup N_1(A^{(k)})) \setminus \widetilde{N}_0(A^{(k)});$ $\widehat{d}_i = 1, i \in \widetilde{N}_0(A^{(k)}); \widehat{d}_i = d, i \in N_2(A^{(k)})\}$, where

$$c = \max_{i \in N_0(A^{(k)}) \bigcup N_1(A^{(k)})} \frac{|a_{ii}^{(k)}| - \xi_i^{(k)}}{\alpha_i^{(k)} + \gamma_i^{(k)} - \xi_i^{(k)}} \ge 1,$$

$$d = \max_{i \in (N_0(A^{(k)}) \bigcup N_1(A^{(k)})) \backslash \widetilde{N}_0(A^{(k)})} \frac{c(|a_{ii}^{(k)}| - \alpha_i^{(k)} - \gamma_i^{(k)} + \xi_i^{(k)}) - \xi_i^{(k)}}{\beta_i^{(k)}} > 0,$$

and write $\widehat{A} = A^{(k)} \widehat{D} = (\widehat{a}_{ij})$.

For $i \in \widetilde{N}_0(A^{(k)})$, we have

$$\begin{aligned} &|\widehat{a}_{ii}| - \widehat{\alpha} - \widehat{\beta} - \widehat{\gamma} \\ &= |a_{ii}^{(k)}| - c\left(\alpha_{i}^{(k)} + \gamma_{i}^{(k)} - \xi_{i}^{(k)}\right) - \xi_{i}^{(k)} - d\beta_{i}^{(k)} \\ &= |a_{ii}^{(k)}| - \xi_{i}^{(k)} - c\left(\alpha_{i}^{(k)} + \gamma_{i}^{(k)} - \xi_{i}^{(k)}\right) \\ &\leq |a_{ii}^{(k)}| - \xi_{i}^{(k)} - \frac{|a_{ii}^{(k)}| - \xi_{i}^{(k)}}{\alpha_{i}^{(k)} + \gamma_{i}^{(k)} - \xi_{i}^{(k)}} (\alpha_{i}^{(k)} + \gamma_{i}^{(k)} - \xi_{i}^{(k)}) = 0. \end{aligned}$$

For $i \in (N_0(A^{(k)}) \bigcup N_1(A^{(k)})) \setminus \widetilde{N}_0(A^{(k)})$, we have

$$\begin{aligned} &|\widehat{a}_{ii}| - \widehat{\alpha} - \widehat{\beta} - \widehat{\gamma} \\ &= c \, |a_{ii}^{(k)}| - c \, (\alpha_i^{(k)} + \gamma_i^{(k)} - \xi_i^{(k)}) - \xi_i^{(k)} - d \, \beta_i^{(k)} \\ &\leq c \, (|a_{ii}^{(k)}| - \alpha_i^{(k)} - \gamma_i^{(k)} + \xi_i^{(k)}) - \xi_i^{(k)} \\ &\quad - \frac{c \, (|a_{ii}^{(k)}| - \alpha_i^{(k)} - \gamma_i^{(k)} + \xi_i^{(k)}) - \xi_i^{(k)}}{\beta_i^{(k)}} \beta_i^{(k)} = 0. \end{aligned}$$

For $i \in N_2(A^{(k)})$, as $c(\alpha_i^{(k)} + \gamma_i^{(k)} - \xi_i^{(k)}) + \xi_i^{(k)} \ge \alpha_i^{(k)} + \gamma_i^{(k)} > 0$, and $d \mid a_{ii}^{(k)} \mid \le d\beta_i^{(k)}$, we have

$$|\widehat{a}_{ii}| - \widehat{\alpha} - \widehat{\beta} - \widehat{\gamma} = d |a_{ii}^{(k)}| - c (\alpha_i^{(k)} + \gamma_i^{(k)} - \xi_i^{(k)}) - \xi_i^{(k)} - d \beta_i^{(k)} < 0.$$

So \widehat{A} has no diagonally dominant row. From Algorithm II, we obtain $\widehat{A} = A^{(k)}\widehat{D} = AD^{(1)}D^{(2)}\cdots D^{(k-1)}\widehat{D}$, where $D^{(1)}D^{(2)}\cdots D^{(k-1)}\widehat{D}$ is a positive diagonal matrix, thus A is not an H-matrix.

(2) We construct a positive diagonal matrix $D = \text{diag}\{d_i \mid d_i = r_i, i \in N_1(A^{(k)}); d_i = 1, i \in N_0(A^{(k)}) \bigcup N_2(A^{(k)})\}$, and write $A' = A^{(k)}D = (a'_{ij})$. For $i \in N_1(A^{(k)})$, we have

$$|a'_{ii}| - \alpha' - \beta' - \gamma' = r_i |a_{ii}^{(k)}| - \sum_{t \in N_1(A^{(k)}), t \neq i} r_t |a_{it}^{(k)}| - \beta_i^{(k)} - \gamma_i^{(k)}$$

$$= h^{(k)} \left(P_i^{(k)} - \sum_{t \in N_1(A^{(k)}), t \neq i} |a_{it}^{(k)}| \frac{P_t^{(k)}}{|a_{tt}^{(k)}|} \right) - \beta_i^{(k)} - \gamma_i^{(k)}$$

$$\geq (\beta_i^{(k)} + \gamma_i^{(k)}) - \beta_i^{(k)} - \gamma_i^{(k)} = 0.$$

For $i \in N_0(A^{(k)}) \bigcup N_2(A^{(k)})$, we have

$$|a'_{ii}| - \alpha' - \beta' - \gamma' = |a^{(k)}_{ii}| - \sum_{t \in N_1(A^{(k)}), t \neq i} r_t |a^{(k)}_{it}| - \beta^{(k)}_i - \gamma^{(k)}_i > 0.$$

So A' is an irreducibly diagonally dominant matrix. From Algorithm II, we obtain $A' = A^{(k)}D = AD^{(1)}D^{(2)}\cdots D^{(k-1)}D$, where $D^{(1)}D^{(2)}\cdots D^{(k-1)}D$ is a positive diagonal matrix, thus A is an H-matrix.

3. Examples

We give the following examples to show the effectiveness of the proposed algorithms:

Example 1. Let

$$A = \left(\begin{array}{ccccccc} 3 & 1 & 1 & 0 & 2 \\ 2 & 4 & 1 & 1 & 1 \\ 0.5 & 0.5 & 3 & 1 & 0.5 \\ 0.5 & 0.25 & 3 & 4 & 0 \\ 1 & 0 & 4 & 0 & 20 \end{array}\right),$$

we have that Algorithm I needs only one iteration for identifying A is an H-matrix, while both Algorithm A and Algorithm A' require three iterations.

Example 2. Let

$$A = \left(egin{array}{ccccc} 1 & 0.1 & 0.05 & 0 \ 0.3 & 1 & 0 & 0.05 \ 0 & 0.05 & 1 & 1.05 \ 0.05 & 0.1 & 1.05 & 1 \end{array}
ight),$$

we have that Algorithm II needs only one iteration for identifying A is not an H-matrix, while Algorithm B requires eleven iterations.

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REFERENCES

- J. Liu, A. He, An interleavede iterative criterion for H-matrices, Int. J. Comput. Math. 186 (2007), 727-734.
- L. Li, H. Niki, M. Sasanabc, A nonparameter criterion for generalized diagonally dominant matrices, Int. J. Comput. Math. 71 (1999), 267-275.
- T. kohno, H. Niki, H. Sawami, Y. Gao, An iterative test for H-matrix, J. Comput. Appl. Math. 115 (2000), 349-355.
- Y. Gao, X. Wang, Criteria for generalized diagonally dominant matrices, Linear Algebra Appl. 169 (1992), 257-268.
- B. Li, L. Li, M. Harada, H. Niki, M. J. Tsatsomeros, An iterative criterion for H-matrices, Linear Algebra Appl. 271 (1998), 179-190.
- T. Huang, X. Zhang, An improved iterative algorithm for generalized diagonally dominant matrices, Int. J.Comput. Math. 181 (2006), 742-746.
- M. Harada, M. Usui, H. Niki, An extension of the criteria for generalized diagonally dominant matrices, Int. J. Comput. Math. 60 (1996), 115-119.
- 8. L. Li, On the iterative criterion for generalized diagonally dominant matrices, Siam J.Matrix Anal. Appl. 24 (2002), 17-21.
- K. Ojiro, H. Niki, M. Usui, A new criteria for the H-matrix Property, J. Comput. Appl. Math. 150 (2003), 293-302.
- 10. R. S Varga, On Recuming theorems on diagonal dominance, Linear Algebra Appl. 13 (1976), 1-9.

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