

Research Article

Some Generalizations and Modifications of Iterative Methods for Solving Large Sparse Symmetric Indefinite Linear Systems

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We discuss a variety of iterative methods that are based on the Arnoldi process for solving large sparse symmetric indefinite linear systems. We describe the SYMMLQ and SYMMQR methods, as well as generalizations and modifications of them. Then, we cover the Lanczos/MSYMLQ and Lanczos/MSYMMQR methods, which arise from a double linear system. We present pseudocodes for these algorithms.

The authors dedicate this paper to the memory of Professor David M. Young, Jr., for his pioneering research, inspirational teaching, and exceptional life

1. Introduction

Frequently, when computing numerical solutions of partial differential equations, one needs to solve systems of very large sparse linear algebraic equations of the form

$$\mathbf{Ax} = \mathbf{b}, \quad (1)$$

where \mathbf{A} is an $n \times n$ matrix, \mathbf{b} is an $n \times 1$ vector, and one seeks a numerical solution vector \mathbf{x} or a good approximation of it. Particularly for large linear systems arising from partial differential equations in three dimensions, well-known direct methods, such as Gaussian elimination, may become prohibitively expensive in terms of both computer storage and computer time. On the other hand, a variety of iterative methods may avoid these difficulties.

For linear systems involving symmetric positive definite (SPD) matrices, the conjugate gradient (CG) method (and variations of it) may work well. On the other hand, when solving linear systems, where the coefficient matrix \mathbf{A} is symmetric indefinite, the choice of a suitable iterative method is not at all clear. On the other hand, the SYMMLQ and MINRES methods have been shown to be useful in certain situations (see Paige and Saunders [1]). For nonsymmetric

systems, Saad and Schultz [2] generalized the MINRES method to obtain the GMRES method.

In Section 2, we review the Arnoldi process. In Sections 3 and 4, we describe the SYMMLQ and SYMMQR methods. Then we can generalize them, in Section 5, and we outline the modified SYMMLQ method, in Section 6. Next, in Section 7, we discuss applying the MSYMLQ and MSYMMQR methods applied to a double linear system. Finally, we present pseudocodes in Sections 8–11.

2. Arnoldi Process

We begin with a review of the Arnoldi process.

Theorem 1. Suppose that \mathbf{A} is an $n \times n$ symmetric matrix. One can generate orthonormal vectors $\mathbf{w}^{(0)}, \mathbf{w}^{(1)}, \dots, \mathbf{w}^{(n-2)}, \mathbf{w}^{(n-1)}$ using this short-term recurrence

$$\begin{aligned} \tilde{\mathbf{w}}^{(j+1)} &\equiv \mathbf{Aw}^{(j)} - \alpha_j \mathbf{w}^{(j)} - \beta_j \mathbf{w}^{(j-1)} \quad (0 \leq j \leq n-2) \\ \mathbf{w}^{(j+1)} &= \left(\frac{1}{\sigma_{j+1}} \right) \tilde{\mathbf{w}}^{(j+1)}, \quad \text{where } \sigma_{j+1} = \sqrt{\langle \tilde{\mathbf{w}}^{(j+1)}, \tilde{\mathbf{w}}^{(j+1)} \rangle}, \end{aligned} \quad (2)$$

7. Lanczos/MSYMLQ Method

Next, we consider this $2n \times 2n$ double linear system:

$$\begin{bmatrix} \mathbf{A} & \mathbf{0} \\ \mathbf{0} & \mathbf{A}^T \end{bmatrix} \begin{bmatrix} \mathbf{x} \\ \widehat{\mathbf{x}} \end{bmatrix} = \begin{bmatrix} \mathbf{b} \\ \widehat{\mathbf{b}} \end{bmatrix}. \quad (86)$$

We obtain the block symmetric matrices \mathcal{A} , \mathcal{E} , and $\mathcal{E}\mathcal{A}$, where

$$\begin{aligned} \mathcal{A} &= \begin{bmatrix} \mathbf{A} & \mathbf{0} \\ \mathbf{0} & \mathbf{A}^T \end{bmatrix}, \\ \mathcal{E} &= \begin{bmatrix} \mathbf{0} & \mathbf{I} \\ \mathbf{I} & \mathbf{0} \end{bmatrix}, \\ \mathcal{E}\mathcal{A} &= \begin{bmatrix} \mathbf{0} & \mathbf{A}^T \\ \mathbf{A} & \mathbf{0} \end{bmatrix}. \end{aligned} \quad (87)$$

For example, the modified SYMMLQ method and the modified SYMMQR method can be applied to the double linear system (86). This leads us to the LAN/MSYMLQ method and the LAN/MSYMMQR method. The pseudocodes for these methods are given in the following sections. For additional details, see Li [3]. See the books by Golub and Van Loan [4] and Saad [5], as well as the papers by Lanczos [6] and Kincaid et al. [7], among others.

8. MSYMLQ Pseudocode

$$\begin{aligned} \mathbf{r}^{(0)} &= \mathbf{b} - \mathbf{A}\mathbf{x}^{(0)}, \\ \beta_1 &= \sqrt{|\langle \mathbf{E}\mathbf{r}^{(0)}, \mathbf{r}^{(0)} \rangle|}, \\ \mathbf{w}^{(1)} &= \left(\frac{1}{\beta_1} \right) \mathbf{r}^{(0)}, \\ d_1 &= \begin{cases} 1, & \text{if } \langle \mathbf{E}\mathbf{r}^{(0)}, \mathbf{E}\mathbf{r}^{(0)} \rangle > 0, \\ -1, & \text{if } \langle \mathbf{E}\mathbf{r}^{(0)}, \mathbf{E}\mathbf{r}^{(0)} \rangle < 0, \end{cases} \\ \varepsilon_1 = \varepsilon_2 = 0, \quad s_0 = 0, \quad c_0 = -1, \\ \alpha_1 &= \left(\frac{1}{d_1} \right) \langle \mathbf{E}\mathbf{A}\mathbf{w}^{(1)}, \mathbf{w}^{(1)} \rangle, \\ \widetilde{\mathbf{w}}^{(2)} &= \mathbf{A}\mathbf{w}^{(1)} - \alpha_1 \mathbf{w}^{(1)}, \\ \beta_2 &= \sqrt{|\langle \mathbf{E}\widetilde{\mathbf{w}}^{(2)}, \widetilde{\mathbf{w}}^{(2)} \rangle|}, \\ \mathbf{w}^{(2)} &= \left(\frac{1}{\beta_2} \right) \widetilde{\mathbf{w}}^{(2)}, \\ d_2 &= \begin{cases} 1, & \text{if } \langle \mathbf{E}\widetilde{\mathbf{w}}^{(2)}, \widetilde{\mathbf{w}}^{(2)} \rangle > 0, \\ -1, & \text{if } \langle \mathbf{E}\widetilde{\mathbf{w}}^{(2)}, \widetilde{\mathbf{w}}^{(2)} \rangle < 0, \end{cases} \\ \widehat{\zeta}_1 &= \frac{\beta_1}{\alpha_1}, \\ \widehat{\mathbf{v}}^{(1)} &= \mathbf{w}^{(1)}, \end{aligned}$$

$$\widehat{\mathbf{x}}^{(1)} = \mathbf{x}^{(0)} + \widehat{\zeta}_1 \mathbf{v}^{(1)},$$

$$c_1 = \frac{d_1 \alpha_1}{\sqrt{\alpha_1^2 + \beta_2^2}}, \quad s_1 = \frac{d_1 \beta_2}{\sqrt{\alpha_1^2 + \beta_2^2}},$$

$$\gamma_1 = (d_1 \alpha_1) c_1 + (d_1 \beta_2) s_1,$$

$$\zeta_1 = \left(\frac{\beta_1}{\gamma_1} \right),$$

$$\mathbf{v}^{(1)} = c_1 \widehat{\mathbf{v}}^{(1)} + s_1 \mathbf{w}^{(2)},$$

$$\mathbf{x}^{(1)} = \mathbf{x}^{(0)} + \zeta_1 \mathbf{v}^{(1)},$$

(88)

for $i = 2, 3, \dots, N$,

$$\alpha_i = \left(\frac{1}{d_i} \right) \langle \mathbf{E}\mathbf{A}\mathbf{w}^{(i)}, \mathbf{w}^{(i)} \rangle,$$

$$\beta_i = \left(\frac{1}{d_{i-1}} \right) \langle \mathbf{E}\mathbf{A}\mathbf{w}^{(i)}, \mathbf{w}^{(i-1)} \rangle,$$

$$\widetilde{\mathbf{w}}^{(i+1)} = \mathbf{A}\mathbf{w}^{(i)} - \alpha_i \mathbf{w}^{(i)} - \beta_i \mathbf{w}^{(i-1)},$$

$$\beta_{i+1} = \sqrt{|\langle \mathbf{E}\widetilde{\mathbf{w}}^{(i+1)}, \widetilde{\mathbf{w}}^{(i+1)} \rangle|},$$

$$\mathbf{w}^{(i+1)} = \left(\frac{1}{\beta_{i+1}} \right) \widetilde{\mathbf{w}}^{(i+1)},$$

$$d_{i+1} = \begin{cases} 1, & \text{if } \langle \mathbf{E}\widetilde{\mathbf{w}}^{(i+1)}, \widetilde{\mathbf{w}}^{(i+1)} \rangle > 0, \\ -1, & \text{if } \langle \mathbf{E}\widetilde{\mathbf{w}}^{(i+1)}, \widetilde{\mathbf{w}}^{(i+1)} \rangle < 0, \end{cases}$$

$$\varepsilon_i = (d_{i-1} \beta_i) s_{i-2}, \quad \delta_i = -(d_{i-1} \beta_i) c_{i-2}, \quad hh = \delta_i,$$

$$\delta_i = (hh) c_{i-1} + (d_i \alpha_i) s_{i-1},$$

$$\widehat{\gamma}_i = (hh) s_{i-1} - (d_i \alpha_i) c_{i-1},$$

$$\widehat{\zeta}_i = \left(\frac{1}{\widehat{\gamma}_i} \right) (-\varepsilon_i \zeta_{i-2} - \delta_i \zeta_{i-1}),$$

$$\widehat{\mathbf{v}}^{(i)} = s_{i-1} \widehat{\mathbf{v}}^{(i-1)} - c_{i-1} \mathbf{w}^{(i)},$$

$$\widehat{\mathbf{x}}^{(i)} = \mathbf{x}^{(i-1)} + \widehat{\zeta}_i \widehat{\mathbf{v}}^{(i)},$$

$$\gamma_i = \sqrt{\alpha_i^2 + \beta_{i+1}^2},$$

$$c_i = d_i \left(\frac{\alpha_i}{\gamma_i} \right), \quad s_i = d_i \left(\frac{\beta_{i+1}}{\gamma_i} \right),$$

$$\zeta_i = \left(\frac{1}{\gamma_i} \right) (-\varepsilon_i \zeta_{i-2} - \delta_i \zeta_{i-1}),$$

$$\mathbf{v}^{(i)} = c_i \widehat{\mathbf{v}}^{(i)} + s_i \mathbf{w}^{(i+1)},$$

$$\mathbf{x}^{(i)} = \mathbf{x}^{(i-1)} + \zeta_i \mathbf{v}^{(i)}$$

end for

(89)

9. MSYMMQR Pseudocode

$$\begin{aligned}
 \mathbf{r}^{(0)} &= \mathbf{b} - \mathbf{A}\mathbf{x}^{(0)}, \\
 \beta_1 &= \sqrt{|\langle \mathbf{E}\mathbf{r}^{(0)}, \mathbf{r}^{(0)} \rangle|}, \\
 \mathbf{w}^{(1)} &= \left(\frac{1}{\beta_1}\right) \mathbf{r}^{(0)}, \\
 d_1 &= \begin{cases} 1, & \text{if } \langle \mathbf{E}\mathbf{r}^{(0)}, \mathbf{E}\mathbf{r}^{(0)} \rangle > 0, \\ -1, & \text{if } \langle \mathbf{E}\mathbf{r}^{(0)}, \mathbf{E}\mathbf{r}^{(0)} \rangle < 0, \end{cases} \\
 \varepsilon_1 = \varepsilon_2 = 0, \quad s_0 = 0, \quad c_0 = 1, \\
 \alpha_1 &= \left(\frac{1}{d_1}\right) \langle \mathbf{E}\mathbf{A}\mathbf{w}^{(1)}, \mathbf{w}^{(1)} \rangle, \\
 \widetilde{\mathbf{w}}^{(2)} &= \mathbf{A}\mathbf{w}^{(1)} - \alpha_1 \mathbf{w}^{(1)}, \\
 \beta_2 &= \sqrt{|\langle \mathbf{E}\widetilde{\mathbf{w}}^{(2)}, \widetilde{\mathbf{w}}^{(2)} \rangle|}, \\
 \mathbf{w}^{(2)} &= \left(\frac{1}{\beta_2}\right) \widetilde{\mathbf{w}}^{(2)}, \\
 d_2 &= \begin{cases} 1, & \text{if } \langle \mathbf{E}\widetilde{\mathbf{w}}^{(2)}, \widetilde{\mathbf{w}}^{(2)} \rangle > 0, \\ -1, & \text{if } \langle \mathbf{E}\widetilde{\mathbf{w}}^{(2)}, \widetilde{\mathbf{w}}^{(2)} \rangle < 0, \end{cases} \\
 \widehat{\zeta}_1 &= \beta_1 d_1, \\
 \widehat{\mathbf{p}}^{(1)} &= \left(\frac{1}{\alpha_1 d_1}\right) \mathbf{w}^{(1)}, \\
 \widehat{\mathbf{x}}^{(1)} &= \mathbf{x}^{(0)} + \widehat{\zeta}_1 \widehat{\mathbf{p}}^{(1)}, \\
 c_1 &= \frac{d_1 \alpha_1}{\sqrt{\alpha_1^2 + \beta_2^2}}, \quad s_1 = -\frac{d_1 \beta_2}{\sqrt{\alpha_1^2 + \beta_2^2}}, \\
 \gamma_1 &= (d_1 \alpha_1) c_1 - (d_1 \beta_2) s_1, \quad \zeta_1 = c_1 \widehat{\zeta}_1, \\
 \mathbf{p}^{(1)} &= \left(\frac{1}{\gamma_1}\right) \mathbf{w}^{(1)}, \\
 \mathbf{x}^{(1)} &= \mathbf{x}^{(0)} + \zeta_1 \mathbf{p}^{(1)}, \\
 \text{for } i &= 2, 3, \dots, N, \\
 \alpha_i &= \left(\frac{1}{d_i}\right) \langle \mathbf{E}\mathbf{A}\mathbf{w}^{(i)}, \mathbf{w}^{(i)} \rangle, \\
 \beta_i &= \left(\frac{1}{d_{i-1}}\right) \langle \mathbf{E}\mathbf{A}\mathbf{w}^{(i)}, \mathbf{w}^{(i-1)} \rangle, \\
 \widetilde{\mathbf{w}}^{(i+1)} &= \mathbf{A}\mathbf{w}^{(i)} - \alpha_i \mathbf{w}^{(i)} - \beta_i \mathbf{w}^{(i-1)}, \\
 \beta_{i+1} &= \sqrt{|\langle \mathbf{E}\widetilde{\mathbf{w}}^{(i+1)}, \widetilde{\mathbf{w}}^{(i+1)} \rangle|}, \\
 \mathbf{w}^{(i+1)} &= \left(\frac{1}{\beta_{i+1}}\right) \widetilde{\mathbf{w}}^{(i+1)},
 \end{aligned}$$

(90)

$$\begin{aligned}
 d_{i+1} &= \begin{cases} 1, & \text{if } \langle \mathbf{E}\widetilde{\mathbf{w}}^{(i+1)}, \widetilde{\mathbf{w}}^{(i+1)} \rangle > 0, \\ -1, & \text{if } \langle \mathbf{E}\widetilde{\mathbf{w}}^{(i+1)}, \widetilde{\mathbf{w}}^{(i+1)} \rangle < 0, \end{cases} \\
 \varepsilon_i &= -(d_{i-1} \beta_i) s_{i-2}, \quad \delta_i = -(d_{i-1} \beta_i) c_{i-2}, \\
 hh &= \delta_i, \\
 \delta_i &= (hh) c_{i-1} - (d_i \alpha_i) s_{i-1}, \\
 \widehat{\gamma}_i &= (hh) s_{i-1} + (d_i \alpha_i) c_{i-1}, \quad \widehat{\zeta}_i = s_{i-1} \widehat{\zeta}_{i-1}, \\
 \widehat{\mathbf{p}}^{(i)} &= \left(\frac{1}{\widehat{\gamma}_i}\right) [\mathbf{w}^{(i)} - \varepsilon_i \mathbf{p}^{(i-2)} - \delta_i \mathbf{p}^{(i-1)}], \\
 \widehat{\mathbf{x}}^{(i)} &= \mathbf{x}^{(i-1)} + \widehat{\zeta}_i \widehat{\mathbf{p}}^{(i)}, \\
 \gamma_i &= \sqrt{\widehat{\zeta}_i^2 + \beta_{i+1}^2}, \\
 c_i &= \frac{\widehat{\gamma}_i}{\gamma_i}, \quad s_i = -\left(\frac{1}{\gamma_i}\right) (d_i \beta_{i+1}), \quad \zeta_i = c_{i-1} \widehat{\zeta}_i, \\
 \mathbf{p}^{(i)} &= \left(\frac{1}{\gamma_i}\right) [\mathbf{w}^{(i)} - \varepsilon_i \mathbf{p}^{(i-2)} - \delta_i \mathbf{p}^{(i-1)}], \\
 \mathbf{x}^{(i)} &= \mathbf{x}^{(i-1)} + \zeta_i \mathbf{p}^{(i)}
 \end{aligned}$$

end for

(91)

10. LAN/MSYMMMLQ Pseudocode

$$\begin{aligned}
 \mathbf{r}^{(0)} &= \mathbf{b} - \mathbf{A}\mathbf{x}^{(0)}, \\
 \widehat{\mathbf{r}}^{(0)} &= \widehat{\mathbf{b}} - \mathbf{A}^T \mathbf{x}^{(0)}, \\
 \beta_1 &= \sqrt{|2\langle \widehat{\mathbf{r}}^{(0)}, \mathbf{r}^{(0)} \rangle|}, \\
 \mathbf{w}^{(1)} &= \left(\frac{1}{\beta_1}\right) \mathbf{r}^{(0)}, \\
 \widehat{\mathbf{w}}^{(1)} &= \left(\frac{1}{\beta_1}\right) \widehat{\mathbf{r}}^{(0)}, \\
 d_1 &= \begin{cases} 1, & \text{if } 2\langle \widehat{\mathbf{r}}^{(0)}, \mathbf{r}^{(0)} \rangle > 0, \\ -1, & \text{if } 2\langle \widehat{\mathbf{r}}^{(0)}, \mathbf{r}^{(0)} \rangle < 0, \end{cases} \\
 \varepsilon_1 = \varepsilon_2 = 0, \quad s_0 = 0, \quad c_0 = -1, \\
 \alpha_1 &= \left(\frac{2}{d_1}\right) \langle \widehat{\mathbf{w}}^{(1)}, \mathbf{w}^{(1)} \rangle, \\
 \widetilde{\mathbf{w}}^{(2)} &= \mathbf{A}\mathbf{w}^{(1)} - \alpha_1 \mathbf{w}^{(1)}, \\
 \widetilde{\widehat{\mathbf{w}}}^{(2)} &= \mathbf{A}^T \widehat{\mathbf{w}}^{(1)} - \alpha_1 \widehat{\mathbf{w}}^{(1)}, \\
 \beta_2 &= \sqrt{|2\langle \widetilde{\widehat{\mathbf{w}}}^{(2)}, \widetilde{\mathbf{w}}^{(2)} \rangle|},
 \end{aligned}$$

$$\begin{aligned}
\mathbf{w}_2 &= \left(\frac{1}{\beta_2} \right) \widetilde{\mathbf{w}}^{(2)}, \\
\widehat{\mathbf{w}}^{(2)} &= \left(\frac{1}{\beta_2} \right) \widetilde{\widehat{\mathbf{w}}}^{(2)}, \\
d_2 &= \begin{cases} 1, & \text{if } 2 \langle \widetilde{\widehat{\mathbf{w}}}^{(2)}, \widetilde{\mathbf{w}}^{(2)} \rangle > 0, \\ -1, & \text{if } 2 \langle \widetilde{\widehat{\mathbf{w}}}^{(2)}, \widetilde{\mathbf{w}}^{(2)} \rangle < 0, \end{cases} \\
\widehat{\zeta}_1 &= \frac{\beta_1}{\alpha_1}, \\
\widehat{\mathbf{v}}^{(1)} &= \mathbf{w}^{(1)}, \\
\widehat{\mathbf{x}}^{(1)} &= \mathbf{x}^{(0)} + \widehat{\zeta}_1 \widehat{\mathbf{v}}^{(1)}, \\
c_1 &= \frac{d_1 \alpha_1}{\sqrt{\alpha_1^2 + \beta_2^2}}, \quad s_1 = \frac{d_1 \beta_2}{\sqrt{\alpha_1^2 + \beta_2^2}}, \\
\gamma_1 &= (d_1 \alpha_1) c_1 + (d_1 \beta_2) s_1, \quad \zeta_1 = \frac{\beta_1}{\gamma_1}, \\
\mathbf{v}^{(1)} &= c_1 \widehat{\mathbf{v}}^{(1)} + s_1 \mathbf{w}^{(2)}, \\
\mathbf{x}^{(1)} &= \mathbf{x}^{(0)} + \zeta_1 \mathbf{v}^{(1)},
\end{aligned} \tag{92}$$

for $i = 2, 3, \dots, N$,

$$\begin{aligned}
\alpha_i &= \left(\frac{2}{d_i} \right) \langle \mathbf{A} \mathbf{w}^{(i)}, \widehat{\mathbf{w}}^{(i)} \rangle, \\
\beta_i &= \left(\frac{1}{d_{i-1}} \right) [\langle \mathbf{A} \mathbf{w}^{(i)}, \widehat{\mathbf{w}}^{(i-1)} \rangle + \langle \widehat{\mathbf{w}}^{(i)}, \mathbf{A} \mathbf{w}^{(i-1)} \rangle], \\
\widetilde{\mathbf{w}}^{(i+1)} &= \mathbf{A} \mathbf{w}^{(i)} - \alpha_i \mathbf{w}^{(i)} - \beta_i \mathbf{w}^{(i-1)}, \\
\widetilde{\widehat{\mathbf{w}}}^{(i+1)} &= \mathbf{A}^T \widehat{\mathbf{w}}^{(i)} - \alpha_i \widehat{\mathbf{w}}^{(i)} - \beta_i \widehat{\mathbf{w}}^{(i-1)}, \\
\beta_{i+1} &= \sqrt{|2 \langle \widetilde{\widehat{\mathbf{w}}}^{(i+1)}, \widetilde{\mathbf{w}}^{(i+1)} \rangle|}, \\
\mathbf{w}^{(i+1)} &= \left(\frac{1}{\beta_{i+1}} \right) \widetilde{\mathbf{w}}^{(i+1)}, \\
\widehat{\mathbf{w}}^{(i+1)} &= \left(\frac{1}{\beta_{i+1}} \right) \widetilde{\widehat{\mathbf{w}}}^{(i+1)}, \\
d_{i+1} &= \begin{cases} 1, & \text{if } 2 \langle \widetilde{\widehat{\mathbf{w}}}^{(i+1)}, \widetilde{\mathbf{w}}^{(i+1)} \rangle > 0, \\ -1, & \text{if } 2 \langle \widetilde{\widehat{\mathbf{w}}}^{(i+1)}, \widetilde{\mathbf{w}}^{(i+1)} \rangle < 0, \end{cases} \\
\varepsilon_i &= d_{i-1} \beta_i s_{i-2}, \quad \delta_i = -(d_{i-1} \beta_i) c_{i-2}, \quad hh = \delta_i, \\
\delta_i &= (hh) c_{i-1} + (d_i \alpha_i) s_{i-1}, \\
\widehat{\gamma}_i &= (hh) s_{i-1} - (d_i \alpha_i) c_{i-1}, \\
\widehat{\zeta}_i &= \left(\frac{1}{\widehat{\gamma}_i} \right) (-\varepsilon_i \zeta_{i-2} - \delta_i \zeta_{i-1}),
\end{aligned}$$

$$\begin{aligned}
\widehat{\mathbf{v}}^{(i)} &= s_{i-1} \widehat{\mathbf{v}}^{(i-1)} - c_{i-1} \mathbf{w}^{(i)}, \\
\widehat{\mathbf{x}}^{(i)} &= \mathbf{x}^{(i-1)} + \widehat{\zeta}_i \widehat{\mathbf{v}}^{(i)}, \\
\gamma_i &= \sqrt{\alpha_i^2 + \beta_{i+1}^2}, \quad c_i = d_i \left(\frac{\alpha_i}{\gamma_i} \right), \quad s_i = d_i \left(\frac{\beta_{i+1}}{\gamma_i} \right), \\
\zeta_i &= \left(\frac{1}{\gamma_i} \right) (-\varepsilon_i \zeta_{i-2} - \delta_i \zeta_{i-1}), \\
\mathbf{v}^{(i)} &= c_i \widehat{\mathbf{v}}^{(i)} + s_i \mathbf{w}^{(i+1)}, \\
\mathbf{x}^{(i)} &= \mathbf{x}^{(i-1)} + \zeta_i \mathbf{v}^{(i)}
\end{aligned}$$

end for

(93)

11. LAN/MSYMMQR Pseudocode

$$\begin{aligned}
\mathbf{r}^{(0)} &= \mathbf{b} - \mathbf{A} \mathbf{x}^{(0)}, \\
\widehat{\mathbf{r}}^{(0)} &= \widehat{\mathbf{b}} - \mathbf{A}^T \mathbf{x}^{(0)}, \\
\beta_1 &= \sqrt{|2 \langle \widehat{\mathbf{r}}^{(0)}, \mathbf{r}^{(0)} \rangle|}, \\
\mathbf{w}^{(1)} &= \left(\frac{1}{\beta_1} \right) \mathbf{r}^{(0)}, \\
\widehat{\mathbf{w}}^{(1)} &= \left(\frac{1}{\beta_1} \right) \widehat{\mathbf{r}}^{(0)}, \\
d_1 &= \begin{cases} 1, & \text{if } 2 \langle \widehat{\mathbf{r}}^{(0)}, \mathbf{r}^{(0)} \rangle > 0, \\ -1, & \text{if } 2 \langle \widehat{\mathbf{r}}^{(0)}, \mathbf{r}^{(0)} \rangle < 0, \end{cases} \\
\varepsilon_1 = \varepsilon_2 = 0, \quad s_0 = 0, \quad c_0 = 1, \\
\alpha_1 &= \left(\frac{2}{d_1} \right) \langle \widehat{\mathbf{w}}^{(1)}, \mathbf{w}^{(1)} \rangle, \\
\widetilde{\mathbf{w}}^{(2)} &= \mathbf{A} \mathbf{w}^{(1)} - \alpha_1 \mathbf{w}^{(1)}, \\
\widetilde{\widehat{\mathbf{w}}}^{(2)} &= \mathbf{A}^T \widehat{\mathbf{w}}^{(1)} - \alpha_1 \widehat{\mathbf{w}}^{(1)}, \\
\beta_2 &= \sqrt{|2 \langle \widetilde{\widehat{\mathbf{w}}}^{(2)}, \widetilde{\mathbf{w}}^{(2)} \rangle|}, \\
\mathbf{w}^{(2)} &= \left(\frac{1}{\beta_2} \right) \widetilde{\mathbf{w}}^{(2)}, \\
\widehat{\mathbf{w}}^{(2)} &= \left(\frac{1}{\beta_2} \right) \widetilde{\widehat{\mathbf{w}}}^{(2)}, \\
d_2 &= \begin{cases} 1, & \text{if } 2 \langle \widetilde{\widehat{\mathbf{w}}}^{(2)}, \widetilde{\mathbf{w}}^{(2)} \rangle > 0 \\ -1, & \text{if } 2 \langle \widetilde{\widehat{\mathbf{w}}}^{(2)}, \widetilde{\mathbf{w}}^{(2)} \rangle < 0 \end{cases}, \\
\widehat{\mathbf{p}}^{(1)} &= \left(\frac{1}{\alpha_i d_i} \right) \mathbf{w}^{(1)},
\end{aligned}$$

$$\begin{aligned} \widehat{\zeta}_1 &= \frac{\beta_1}{\alpha_1}, \\ \widehat{\mathbf{x}}^{(1)} &= \mathbf{x}^{(0)} + \widehat{\zeta}_1 \widehat{\mathbf{p}}^{(1)}, \\ c_1 &= \frac{d_1 \alpha_1}{\sqrt{\alpha_1^2 + \beta_2^2}}, \quad s_1 = -\frac{d_1 \beta_2}{\sqrt{\alpha_1^2 + \beta_2^2}}, \\ \gamma_1 &= (d_1 \alpha_1) c_1 - (d_1 \beta_2) s_1, \\ \widehat{\gamma}_1 &= \beta_1 \widehat{\gamma}_1, \\ \mathbf{p}^{(1)} &= \left(\frac{1}{\gamma_1}\right) \mathbf{w}^{(1)}, \\ \mathbf{x}^{(1)} &= \mathbf{x}^{(0)} + \zeta_1 \mathbf{p}^{(1)}, \end{aligned} \tag{94}$$

for $i = 2, 3, \dots, N$,

$$\begin{aligned} \alpha_i &= \left(\frac{2}{d_i}\right) \langle \mathbf{A}\mathbf{w}^{(i)}, \widehat{\mathbf{w}}^{(i)} \rangle, \\ \beta_i &= \left(\frac{1}{d_{i-1}}\right) \left[\langle \mathbf{A}\mathbf{w}^{(i)}, \widehat{\mathbf{w}}^{(i-1)} \rangle + \langle \widehat{\mathbf{w}}^{(i)}, \mathbf{A}\mathbf{w}^{(i-1)} \rangle \right], \\ \widehat{\mathbf{w}}^{(i+1)} &= \mathbf{A}\mathbf{w}^{(i)} - \alpha_i \mathbf{w}^{(i)} - \beta_i \mathbf{w}^{(i-1)}, \\ \widetilde{\widehat{\mathbf{w}}}^{(i+1)} &= \mathbf{A}^T \widehat{\mathbf{w}}^{(i)} - \alpha_i \widehat{\mathbf{w}}^{(i)} - \beta_i \widehat{\mathbf{w}}^{(i-1)}, \\ \beta_{i+1} &= \sqrt{|2 \langle \widetilde{\widehat{\mathbf{w}}}^{(i+1)}, \widehat{\mathbf{w}}^{(i+1)} \rangle|}, \\ \mathbf{w}^{(i+1)} &= \left(\frac{1}{\beta_{i+1}}\right) \widetilde{\widehat{\mathbf{w}}}^{(i+1)}, \\ \widehat{\mathbf{w}}^{(i+1)} &= \left(\frac{1}{\beta_{i+1}}\right) \widehat{\mathbf{w}}^{(i+1)}, \\ d_{i+1} &= \begin{cases} 1, & \text{if } 2 \langle \widetilde{\widehat{\mathbf{w}}}^{(i+1)}, \widehat{\mathbf{w}}^{(i+1)} \rangle > 0, \\ -1, & \text{if } 2 \langle \widetilde{\widehat{\mathbf{w}}}^{(i+1)}, \widehat{\mathbf{w}}^{(i+1)} \rangle < 0, \end{cases} \\ \varepsilon_i &= (d_{i-1} \beta_i) s_{i-2}, \quad \delta_i = (d_{i-1} \beta_i) c_{i-2}, \quad hh = \delta_i, \\ \delta_i &= (hh) c_{i-1} - d_i (\alpha_i s_{i-1}), \\ \widehat{\gamma}_i &= (hh) s c_{i-1} + d_i (\alpha_i c_{i-1}), \\ \widehat{\zeta}_i &= \widetilde{\zeta}_{i-1} s_{i-1}, \\ \widehat{\mathbf{p}}^{(i)} &= \left(\frac{1}{\widehat{\gamma}_i}\right) \left[\mathbf{w}^{(i)} - \varepsilon_i \mathbf{p}^{(i)} - \delta_i \mathbf{p}^{(i-1)} \right], \\ \widehat{\mathbf{x}}^{(i)} &= \mathbf{x}^{(i-1)} + \widehat{\zeta}_i \widehat{\mathbf{p}}^{(i)}, \\ \gamma_i &= \sqrt{\widehat{\gamma}^2 + \beta_{i+1}^2}, \\ c_i &= \left(\frac{\widehat{\gamma}_i}{\gamma_i}\right), \quad s_i = -d_i \left(\frac{\beta_{i+1}}{\gamma_i}\right), \\ \zeta_i &= c_i \widehat{\zeta}_i, \end{aligned}$$

$$\begin{aligned} \mathbf{p}^{(i)} &= \left(\frac{1}{\gamma_i}\right) \left[\mathbf{w}^{(i)} - \varepsilon_i \mathbf{p}^{(i-2)} - \delta_i \mathbf{p}^{(i-1)} \right], \\ \mathbf{x}^{(i)} &= \mathbf{x}^{(i-1)} + \zeta_i \mathbf{p}^{(i)} \end{aligned}$$

end for

(95)

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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