

# Research on a Class of Nonlinear Matrix Equation

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**Abstract.** In this paper, the nonlinear matrix equation  $X^r + \sum_{i=1}^m A_i^* X^{\delta_i} A_i = Q$  is discussed. We propose the Newton iteration method for obtaining the Hermite positive definite solution of this equation. And a numerical example is given to identify the efficiency of the results obtained.

**Keywords:** Nonlinear matrix equation, Positive definite solution, Iteration, Convergence.

## 1 Introduction

Consider the nonlinear matrix equation

$$X + A^* X^{-1} A = Q. \quad (1)$$

Zhan [5] have studied that the maximal positive definite solution of Eq.(1) with the case  $Q = I$ . An iterative method for obtaining the maximal positive definite solutions of Eq.(1) is proposed. The convergence of the iterative method is also discussed in his paper. Simultaneously, Zhan and Xie [8] have proved that a necessary and sufficient condition for the existence of solutions of Eq.(1) in which  $A$  should satisfy the following demands :  $A = P^T \Gamma Q \Sigma P$ , where  $P$ ,  $Q$  are orthogonal matrices, and diagonal matrix  $\Gamma$  and  $\Sigma$  satisfy  $\Gamma > 0$ ,  $\Sigma \geq 0$ ,  $\Gamma^2 + \Sigma^2 = I$ . Meanwhile, the solution of Eq.(1) and some necessary conditions for the existence of the solution of the nonlinear matrix equation are given. When  $Q = I$  and  $A$  is real matrix, Engwerda [2] have used a simple recursion algorithm to obtain the solution of Eq.(1) and proposed a sufficient and necessary condition for the existence of a positive definite solution.

In this paper, we study Newton iteration method for obtaining Hermite positive definite solutions of equation

$$X + \sum_{i=1}^m A_i^* X^{-1} A_i = Q, \quad (2)$$

where  $A_i$  is a nonsingular matrix,  $Q$  is a Hermite positive definite matrix,  $r, m$  are positive integer and  $-1 < \delta_i < 0 (i = 1, 2, \dots, m)$ .

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## 2 Newton’s Method for Obtaining Hermite Positive Definite Solutions of the Matrix Equation

$$X + \sum_{i=1}^m A_i^* X^{-1} A_i = Q$$

In this section, we study Newton’s method for obtaining Hermite positive definite solutions of matrix equation  $X + \sum_{i=1}^m A_i^* X^{-1} A_i = Q$ , where  $A_i$  is a nonsingular complex matrix and  $Q$  is a Hermite definite matrix.

### 2.1 Related Lemmas

**Lemma 1.** [6] Let  $\sum_{i=1}^m \|Q^{-\frac{1}{2}} A_i Q^{-\frac{1}{2}}\|^2 < \frac{1}{4}$ , and define a matrix set  $T = \{X | \beta_1 Q \leq X \leq \beta_2 Q\}$ . Thus Eq.(2) has a unique solution in  $T$ , where  $\beta_1$  is a larger root of this equation  $x(1-x) = \lambda_{max}(\sum_{i=1}^m Q^{-\frac{1}{2}} A_i^* Q^{-1} A_i Q^{-\frac{1}{2}})$  and  $\beta_2$  is a larger root of equation  $x(1-x) = \lambda_{min}(\sum_{i=1}^m Q^{-\frac{1}{2}} A_i^* Q^{-1} A_i Q^{-\frac{1}{2}})$ .

**Lemma 2.** [1] Let  $B_i \in C^{n \times n}$ , and  $P, Q \in H_+^{n \times n}$ . If  $\sum_{i=1}^m \|Q^{\frac{1}{2}} B_i Q^{-\frac{1}{2}}\|^2 < 1$ , then this matrix equation  $X - \sum_{i=1}^m B_i^* X B_i = P$  has a unique solution  $X$ , and  $X \geq 0$ .

**Lemma 3.** [4] Let  $B_i \in C^{n \times n}, P, Q, C \in H_+^{n \times n}$ . If  $\sum_{i=1}^m \|Q^{-\frac{1}{2}} B_i^* C^{-1} Q^{\frac{1}{2}}\|^2 < 1$ , the matrix equation  $C^* X C - \sum_{i=1}^m B_i^* X B_i = P$  has a unique solution  $X$ , and  $X \geq 0$ .

**Lemma 4.** [7] If  $C$  and  $P$  are the same order Hermite equations, and  $P > 0$ , then  $CPC + P^{-1} \geq 2C$ .

**Lemma 5.** [3] If  $F \in R^{n \times m}$ , and  $\|F\|_p < 1$ , then  $I - F$  is nonsingular. Moreover  $(I - F)^{-1} = \sum_{k=0}^{\infty} F^k$ . Further  $\|(I - F)^{-1}\|_p \leq \frac{1}{1 - \|F\|_p}$ .

### 2.2 Newton Iteration Method for Solving the Matrix Equation

$$X + \sum_{i=1}^m A_i^* X^{-1} A_i = Q$$

Newton iteration construction process is given firstly. For matrix function

$$F(X) = Q - X - \sum_{i=1}^m A_i^* X^{-1} A_i. \tag{3}$$

Let  $H = X_{n+1} - X_n$ . We have

$$\begin{aligned}
 & F(X + H) - F(X) \\
 &= \sum_{i=1}^m A_i^* [X^{-1} - (X + H)^{-1}] A_i - H \\
 &= \sum_{i=1}^m A_i^* (X + H)^{-1} H X^{-1} A_i - H \\
 &= \sum_{i=1}^m A_i^* [(X + H)^{-1} - X^{-1}] H X^{-1} A_i + \sum_{i=1}^m A_i^* X^{-1} H X^{-1} A_i - H \\
 &= - \sum_{i=1}^m A_i^* X^{-1} H (X + H)^{-1} H X^{-1} A_i + \sum_{i=1}^m A_i^* X^{-1} H X^{-1} A_i - H.
 \end{aligned}$$

For the definition of Frechet derivative, we know that

$$F'(X)H = \sum_{i=1}^m A_i^* X^{-1} H X^{-1} A_i - H \tag{4}$$

by Newton's formula

$$F'(X_n)H = -F(X_n). \tag{5}$$

Therefore

$$X_{n+1} - \sum_{i=1}^m A_i^* X_n^{-1} X_{n+1} X_n^{-1} A_i = Q - 2 \sum_{i=1}^m A_i^* X_n^{-1} A_i. \tag{6}$$

Hence we can get the iterative algorithm:

$$\{ X_0 \in [\frac{1}{2}Q, Q], X_{n+1} - \sum_{i=1}^m A_i^* X_n^{-1} X_{n+1} X_n^{-1} A_i = Q - 2 \sum_{i=1}^m A_i^* X_n^{-1} A_i. \tag{7}$$

**Theorem 1.** Let  $\sum_{i=1}^m \|Q^{-\frac{1}{2}} A_i Q^{-\frac{1}{2}}\|^2 < \frac{1}{4}$ ,  $\{X_n\}$  is matrix sequence which is determined by the iterative Algorithm (7), then  $X_n \in [\frac{1}{2}Q, Q]$ , and

$$\sum_{i=1}^m \|Q^{-\frac{1}{2}} A_i^* X_n^{-1} Q^{\frac{1}{2}}\|^2 < 1.$$

*Proof.* For  $\sum_{i=1}^m \|Q^{-\frac{1}{2}} A_i Q^{-\frac{1}{2}}\|^2 < \frac{1}{4}$ , so

$$\sum_{i=1}^m \|Q^{-\frac{1}{2}} A_i Q^{-\frac{1}{2}}\|^2 I = \sum_{i=1}^m \lambda_{\max}(Q^{-\frac{1}{2}} A_i^* Q^{-1} A_i Q^{-\frac{1}{2}}) I \geq \sum_{i=1}^m Q^{-\frac{1}{2}} A_i^* Q^{-1} A_i Q^{-\frac{1}{2}}.$$

Hence

$$0 \leq \sum_{i=1}^m Q^{-\frac{1}{2}} A_i^* Q^{-1} A_i Q^{-\frac{1}{2}} < \frac{1}{4} I.$$

Similarly, we get

$$\begin{aligned}
 & \sum_{i=1}^m \|Q^{-\frac{1}{2}} A_i^* X_n^{-1} Q^{\frac{1}{2}}\|^2 I \\
 \geq & \sum_{i=1}^m Q^{\frac{1}{2}} X_n^{-1} A_i Q^{-1} A_i^* X_n^{-1} Q^{\frac{1}{2}} \\
 = & \sum_{i=1}^m (Q^{\frac{1}{2}} X_n^{-1} Q^{\frac{1}{2}}) (Q^{-\frac{1}{2}} A_i Q^{-1} A_i^* Q^{-\frac{1}{2}}) (Q^{\frac{1}{2}} X_n^{-1} Q^{\frac{1}{2}}) \\
 = & (Q^{\frac{1}{2}} X_n^{-1} Q^{\frac{1}{2}}) \left[ \sum_{i=1}^m (Q^{-\frac{1}{2}} A_i Q^{-1} A_i^* Q^{-\frac{1}{2}}) \right] (Q^{\frac{1}{2}} X_n^{-1} Q^{\frac{1}{2}}).
 \end{aligned}$$

Then by  $X_n \in [\frac{1}{2}Q, Q]$ , we can obtain  $I \leq Q^{\frac{1}{2}} X_n^{-1} Q^{\frac{1}{2}} \leq 2I$ . There is

$$\sum_{i=1}^m \|Q^{-\frac{1}{2}} A_i^* X_n^{-1} Q^{\frac{1}{2}}\|^2 I \leq I.$$

Hence

$$\sum_{i=1}^m \|Q^{-\frac{1}{2}} A_i^* X_n^{-1} Q^{\frac{1}{2}}\|^2 < 1.$$

We will prove  $X_{n+1} \in [\frac{1}{2}Q, Q]$  using the inductive method as follow.

If  $k = 0$ , according to known, we can obtain  $x_0 \in [\frac{1}{2}Q, Q]$ .

Assume that  $k = n$ ,  $X_n \in [\frac{1}{2}Q, Q]$ ,  $\forall n \in \mathbb{N}$ . We know  $k = n + 1$ ,  $X_{n+1} \in [\frac{1}{2}Q, Q]$ .

The Eq.(6) can become

$$Q - X_{n+1} - \sum_{i=1}^m A_i^* X_n^{-1} (Q - X_{n+1}) X_n^{-1} A_i = \sum_{i=1}^m A_i^* X_n^{-1} (2X_n - Q) X_n^{-1} A_i. \tag{8}$$

According to  $X_n \in [\frac{1}{2}Q, Q]$ , that is  $2X_n - Q \geq 0$ . We can deduce

$$A_i^* X_n^{-1} (2X_n - Q) X_n^{-1} A_i \geq 0, \quad \forall i = 1, 2, \dots, m.$$

That is

$$\sum_{i=1}^m A_i^* X_n^{-1} (2X_n - Q) X_n^{-1} A_i \geq 0.$$

Thus from Lemma 2, we get  $Q - X_{n+1} \geq 0$ . That is  $X_{n+1} \leq Q$ .

Similarly, the matrix Eq.(6) can also become

$$\begin{aligned}
 & X_{n+1} - \frac{1}{2}Q - \sum_{i=1}^m A_i^* X_n^{-1} (X_{n+1} - \frac{1}{2}Q) X_n^{-1} A_i \\
 = & \frac{1}{2}Q - \sum_{i=1}^m A_i^* (2X_n^{-1} - \frac{1}{2}X_n^{-1} Q X_n^{-1}) A_i.
 \end{aligned} \tag{9}$$

From  $X_n \in [\frac{1}{2}Q, Q]$ , we can obtain  $Q^{-\frac{1}{2}} X_n Q^{-\frac{1}{2}} \in [\frac{1}{2}I, I]$ , and

$$2(Q^{-\frac{1}{2}} X_n Q^{-\frac{1}{2}})^{-1} - \frac{1}{2}(Q^{-\frac{1}{2}} X_n Q^{-\frac{1}{2}})^{-2} \in [\frac{2}{3}I, 2I].$$

Hence

$$\begin{aligned}
 & \sum_{i=1}^m A_i^* (2X_n^{-1} - \frac{1}{2}X_n^{-1}QX_n^{-1})A_i \\
 = & \sum_{i=1}^m Q^{\frac{1}{2}} (Q^{-\frac{1}{2}}A_i^*Q^{-\frac{1}{2}}) [2(Q^{-\frac{1}{2}}X_nQ^{-\frac{1}{2}})^{-1} - \frac{1}{2}(Q^{-\frac{1}{2}}X_nQ^{-\frac{1}{2}})^{-2}] (Q^{-\frac{1}{2}}A_iQ^{-\frac{1}{2}})Q^{\frac{1}{2}} \\
 \leq & 2 \sum_{i=1}^m A_i^*Q^{-1}A_i \\
 \leq & \frac{1}{2}Q.
 \end{aligned}$$

So the right side of Eq.(9) is positive semi-definite. Hence,

$$X_{n+1} \geq \frac{1}{2}Q.$$

In conclusion,  $\forall n = 0, 1, \dots$ , we have  $X_n \in [\frac{1}{2}Q, Q]$ , and

$$\sum_{i=1}^m \|Q^{-\frac{1}{2}}A_i^*X_n^{-1}Q^{\frac{1}{2}}\|^2 < 1.$$

□

**Theorem 2.** For iterative Algorithm(7), if  $\sum_{i=1}^m \|Q^{-\frac{1}{2}}A_iQ^{-\frac{1}{2}}\|^2 < \frac{1}{4}$ , then we have

$$X_1 \geq X_2 \geq \dots \geq X_n \geq \dots. \tag{10}$$

*Proof.* According to Newton iterative Eq.(5), for any  $n \geq 1$ , we have

$$X_n - X_{n+1} - \sum_{i=1}^m A_i^*X_n^{-1}(X_n - X_{n+1})X_n^{-1}A_i = X_n + \sum_{i=1}^m A_i^*X_n^{-1}A_i - Q.$$

Since  $\sum_{i=1}^m \|Q^{-\frac{1}{2}}A_i^*X_n^{-1}Q^{\frac{1}{2}}\|^2 < 1$ , if we can prove  $X_n + \sum_{i=1}^m A_i^*X_n^{-1}A_i - Q \geq 0$ , then we can get  $X_n - X_{n+1} \geq 0$  directly.

Consider the Eq.(6)

$$\sum_{i=1}^m A_i^*X_{n-1}^{-1}X_nX_{n-1}^{-1}A_i - 2 \sum_{i=1}^m A_i^*X_{n-1}^{-1}A_i - X_n + Q = 0.$$

Then

$$\begin{aligned}
 & X_n + \sum_{i=1}^m A_i^*X_n^{-1}A_i - Q \\
 = & \sum_{i=1}^m A_i^*X_{n-1}^{-1}X_nX_{n-1}^{-1}A_i + \sum_{i=1}^m A_i^*X_n^{-1}A_i - 2 \sum_{i=1}^m A_i^*X_{n-1}^{-1}A_i \\
 = & \sum_{i=1}^m A_i^*X_{n-1}^{-1}(X_n - X_{n-1})X_{n-1}^{-1}A_i + \sum_{i=1}^m A_i^*X_{n-1}^{-1}(X_{n-1} - X_n)X_n^{-1}A_i \\
 = & \sum_{i=1}^m A_i^*X_{n-1}^{-1}(X_{n-1} - X_n)X_n^{-1}(X_{n-1} - X_n)X_{n-1}^{-1}A_i \\
 \geq & 0.
 \end{aligned}$$

So  $X_n - X_{n+1} \geq 0, \forall n = 1, 2, \dots$

□

**Theorem 3.** Consider the iterative Algorithm(7). If  $\sum_{i=1}^m \|Q^{-\frac{1}{2}}A_iQ^{-\frac{1}{2}}\|^2 < \frac{1}{4}$ , then the iterative sequence  $\{X_n\}$  converges to  $X_L$ .

*Proof.* According to Theorem 1 and Theorem 2, in Newton iterative method, for  $\forall n \in N$ , we get  $X_n \in [\frac{1}{2}Q, Q]$ , and  $\{X_n\}$  is bounded monotonic sequence. Hence, for enough  $n$ ,  $\{X_n\}$  converges to  $X$ , and  $X$  is a solution of the Eq.(2). Let  $X_n \rightarrow X'$ ,  $X'$  is a solution of the Eq.(2), then we have  $X' \leq X_L$ . On the other hand, notice that  $X'$  is obtained by sequence  $\{X_n\}$ , for the any solution  $X$  of the Eq.(2), we will prove that  $X_n \geq X, \forall n \geq 1$  as follow. Eq.(6) then becomes

$$\begin{aligned} X_{n+1} - X &= \sum_{i=1}^m A_i^* X_n^{-1} (X_{n+1} - X) X_n^{-1} A_i \\ &= Q - 2 \sum_{i=1}^m A_i^* X_n^{-1} A_i - X + \sum_{i=1}^m A_i^* X_n^{-1} X X_n^{-1} A_i. \end{aligned}$$

According to  $X$  is a solution of Eq.(2), then  $X$  satisfies  $X + \sum_{i=1}^m A_i^* X^{-1} A_i = Q$ .

Therefore

$$\begin{aligned} X_{n+1} - X &= \sum_{i=1}^m A_i^* X_n^{-1} (X_{n+1} - X) X_n^{-1} A_i \\ &= \sum_{i=1}^m A_i^* X^{-1} A_i + \sum_{i=1}^m A_i^* X_n^{-1} X X_n^{-1} A_i - 2 \sum_{i=1}^m A_i^* X_n^{-1} A_i \\ &= \sum_{i=1}^m A_i^* X^{-1} (X_n - X) X_n^{-1} A_i - \sum_{i=1}^m A_i^* X_n^{-1} (X_n - X) X_n^{-1} A_i \\ &= \sum_{i=1}^m A_i^* X_n^{-1} (X_n - X) X^{-1} (X_n - X) X_n^{-1} A_i \geq 0. \end{aligned}$$

According to Lemma 2, whether or not  $X_n - X$  is positive definite, we can obtain  $X_{n+1} - X \geq 0$ . In fact, by  $X_n \geq X, n = 1, 2, \dots$ , we can obtain  $X_n \geq X_L, n = 1, 2, \dots$ , and  $X' \geq X_L$ .

In conclusion, we have  $X' = X_L$ , it is equivalent to  $\lim_{n \rightarrow \infty} X_n = X_L$ . □

**Theorem 4.** If  $\sum_{i=1}^m \|Q^{-\frac{1}{2}}A_iQ^{-\frac{1}{2}}\|^2 < \frac{1}{4}$ , then the matrix sequence  $\{X_n\}$  of Algorithm (7) satisfies

$$\|X_{n+1} - X_L\| \leq \frac{4 \sum_{i=1}^m \lambda \max(Q^{-\frac{1}{2}}A_i^*Q^{-1}A_iQ^{-\frac{1}{2}}) \|Q^{-\frac{1}{2}}\|^2 \cdot \|Q^{\frac{1}{2}}\|^2}{\beta_1(1-4 \sum_{i=1}^m \lambda \max(Q^{-\frac{1}{2}}A_i^*Q^{-1}A_iQ^{-\frac{1}{2}}))} \|X_n - X_L\|^2, \quad (11)$$

where  $\beta_1 = \frac{1 + \sqrt{1 - 4 \lambda \max(\sum_{i=1}^m Q^{-\frac{1}{2}}A_i^*Q^{-1}A_iQ^{-\frac{1}{2}})}}{2}$ .

*Proof.* Obviously, from Lemma 1 and Theorem 3, we know that the maximal solution  $X_L$  of Eq.(2) satisfies  $X_L \in (\beta_1Q, \beta_2Q)$ , and  $Q = X_L + \sum_{i=1}^m A_i^* X_L^{-1} A_i$ ,

then

$$\|Q^{\frac{1}{2}}X_L^{-1}Q^{\frac{1}{2}}\| \leq \frac{1}{\beta_1},$$

where  $\beta_1$  is a large root of equation  $x(1-x) = \lambda \max(\sum_{i=1}^m Q^{-\frac{1}{2}}A_i^*Q^{-1}A_iQ^{-\frac{1}{2}})$ .

Therefore, we can obtain

$$\beta_1 = \frac{1 + \sqrt{1 - 4\lambda \max(\sum_{i=1}^m Q^{-\frac{1}{2}}A_i^*Q^{-1}A_iQ^{-\frac{1}{2}})}}{2}.$$

In Eq.(6), we use  $X_L + \sum_{i=1}^m A_i^*X_L^{-1}A_i$  to replace  $Q$ , then

$$\sum_{i=1}^m A_i^*X_n^{-1}X_{n+1}X_n^{-1}A_i - 2\sum_{i=1}^m A_i^*X_n^{-1}A_i - X_{n+1} + X_L + \sum_{i=1}^m A_i^*X_L^{-1}A_i = 0.$$

So

$$\begin{aligned} & X_{n+1} - X_L \\ &= \sum_{i=1}^m A_i^*X_n^{-1}(X_{n+1} - X_n)X_n^{-1}A_i + \sum_{i=1}^m A_i^*X_n^{-1}(X_n - X_L)X_L^{-1}A_i \\ &= \sum_{i=1}^m A_i^*X_n^{-1}(X_{n+1} - X_L)X_L^{-1}A_i - \sum_{i=1}^m A_i^*X_n^{-1}(X_n - X_L)X_n^{-1}A_i \\ &\quad + \sum_{i=1}^m A_i^*X_n^{-1}(X_n - X_L)X_L^{-1}A_i \\ &= \sum_{i=1}^m A_i^*X_n^{-1}(X_{n+1} - X_L)X_n^{-1}A_i \\ &\quad + \sum_{i=1}^m A_i^*X_n^{-1}(X_n - X_L)X_L^{-1}(X_n - X_L)X_n^{-1}A_i. \end{aligned}$$

Since  $X_n \in [\frac{1}{2}Q, Q]$ , then

$$\|Q^{\frac{1}{2}}X_n^{-1}Q^{\frac{1}{2}}\| \leq 2.$$

So

$$\begin{aligned} & \|Q^{-\frac{1}{2}}(X_{n+1} - X_L)Q^{-\frac{1}{2}}\| \\ & \leq (\sum_{i=1}^m \|Q^{-\frac{1}{2}}A_iQ^{-\frac{1}{2}}\|^2) \|Q^{\frac{1}{2}}X_n^{-1}Q^{\frac{1}{2}}\|^2 \|Q^{-\frac{1}{2}}(X_{n+1} - X_L)Q^{-\frac{1}{2}}\|^2 \\ & + (\sum_{i=1}^m \|Q^{-\frac{1}{2}}A_iQ^{-\frac{1}{2}}\|^2) \|Q^{\frac{1}{2}}X_n^{-1}Q^{\frac{1}{2}}\|^2 \|Q^{\frac{1}{2}}X_L^{-1}Q^{\frac{1}{2}}\|^2 \|Q^{-\frac{1}{2}}(X_{n+1} - X_L)Q^{-\frac{1}{2}}\|^2 \\ & \leq 4 \sum_{i=1}^m \lambda \max(Q^{-\frac{1}{2}}A_i^*Q^{-1}A_iQ^{-\frac{1}{2}}) \|Q^{-\frac{1}{2}}(X_{n+1} - X_L)Q^{-\frac{1}{2}}\|^2 \\ & + \frac{4 \sum_{i=1}^m \lambda \max(Q^{-\frac{1}{2}}A_i^*Q^{-1}A_iQ^{-\frac{1}{2}})}{\beta_1} \|Q^{-\frac{1}{2}}\|^2 \|X_n - X_L\|^2. \end{aligned}$$

And then we obtain

$$\begin{aligned} \|X_{n+1} - X_L\| & \leq \|Q^{\frac{1}{2}}\|^2 \cdot \|Q^{-\frac{1}{2}}(X_{n+1} - X_L)Q^{-\frac{1}{2}}\| \\ & \leq \frac{4 \sum_{i=1}^m \lambda \max(Q^{-\frac{1}{2}}A_i^*Q^{-1}A_iQ^{-\frac{1}{2}}) \|Q^{-\frac{1}{2}}\|^2 \cdot \|Q^{\frac{1}{2}}\|^2}{\beta_1(1-4 \sum_{i=1}^m \lambda \max(Q^{-\frac{1}{2}}A_i^*Q^{-1}A_iQ^{-\frac{1}{2}}))} \|X_n - X_L\|^2, \end{aligned}$$

where  $\beta_1 = \frac{1 + \sqrt{1 - 4\lambda \max_{i=1}^m Q^{-\frac{1}{2}} A_i^* Q^{-1} A_i Q^{-\frac{1}{2}}}}{2}$ . □

By this theorem, we know, if  $\sum_{i=1}^m \|Q^{-\frac{1}{2}} A_i Q^{-\frac{1}{2}}\|^2 < \frac{1}{4}$  and the condition of this select initial original  $X_0 \in [\frac{1}{2}Q, Q]$ , the constructed Newton iterative convergence is quadratic.

### 3 Numerical Examples

In this section, we will give a numerical example to identify the two algorithm of achieve extremal positive definite solutions of the equation. For different matrices  $A_i$  and different  $\alpha, r, \delta_i, i = 1, 2, \dots, m$ . We compute the solutions of the equation

$$X + \sum_{i=1}^m A_i^* X^{\delta_i} A_i = Q.$$

We will operate all programs by using MATLAB 7.0. We note that

$$\varepsilon(X_k) = \|X_k^r + \sum_{i=1}^m A_i^* X_k^{\delta_i} A_i - Q\|.$$

*Example 1.* We consider the equation by using the two matrices  $A_1$  and  $A_2$  as follows:

$$A_1 = 0.5 * \begin{pmatrix} -0.1 & 0.2 & -0.06 \\ 0.2 & -0.3 & 0.16 \\ -0.1 & 0 & 0.02 \end{pmatrix}, \quad A_2 = \begin{pmatrix} 0.01 & 0.02 & 0.03 \\ 0.01 & 0.225 & 0.12 \\ 0 & 0.09 & 0.07 \end{pmatrix},$$

where  $Q = I, r = 5, \delta_1 = -\frac{1}{3}, \delta_2 = -\frac{1}{4}$ .

By Algorithm 7, the following table records the different values of parameter  $\alpha (\alpha > 1)$ , and the values satisfy the number of iterations which is needed by a stop condition.

**Table 1.**

$\alpha$	k		
	$tol = 10^{-4}$	$tol = 10^{-6}$	$tol = 10^{-8}$
1.3	3	4	5
1.5	3	4	5
1.7	3	4	5
2.1	3	4	5

$$X_L = \begin{pmatrix} 0.9969 & 0.0037 & -0.0021 \\ 0.0037 & 0.9808 & -0.0040 \\ -0.0021 & -0.0040 & 0.9943 \end{pmatrix}, \quad X_L - D = \begin{pmatrix} 0.9969 & 0.0037 & -0.0021 \\ 0.0037 & 0.9808 & -0.0040 \\ -0.0021 & -0.0040 & 0.9943 \end{pmatrix},$$

where  $D = \frac{1}{2} \sum_{i=1}^2 (A_i Q^{-1} A_i^*)^{-\frac{1}{\delta_i}}$ .



The eigenvalue of  $X_L - D$  is (0.9791, 0.9995, 0.9933).

The eigenvalue of  $Q^{\frac{1}{5}} - X_L$  is (0.0005, 0.0067, 0.0208).

It implies that  $X_L \in \Omega$ .

From the Table 1, we conclude that the number of iterations increased with increasing of  $\alpha$  within some extent errors.

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## References

1. Bhatia, R.: Matrix Analysis M. Springer, Berlin (1997)
2. Engwerda, J.C.: On the existence of a positive definite solution of the matrix equation  $X + A^T X^{-1} A = I$ . Linear Algebra Appl. 194, 91–108 (1993)
3. Golub, G.H., Loan, C.F.: Matrix computations. Johns Hopkins University Press (2012)
4. Ramadan., M.A., El-Shazly, N.M.: On the matrix equation  $X + A^* \sqrt[m]{X^{-1}} A = I$ . J. Appl. Math. Comput. 173, 992–1013 (2006)
5. Xu, S.F.: On the maximal solution of the matrix equation  $X + A^T X^{-1} A = I$ . J. Beijing Univ. 36(1), 29–38 (2000)
6. Duan, X.F., Liao, A.P.: On the existence of Hermitian positive definite solutions of the matrix equation  $X^s + A^* X^{-t} A = Q$ . J. Linear Algebra Appl. 429, 673–687 (2008)
7. Zhan, X.: Computing the extremal positive definite solutions of a matrix equation. SIAM J. Sci. Comput. 17, 1167–1174 (1996)
8. Zhan, X.Z., Xie, J.J.: On the matrix equation  $X + A^T X^{-1} A = I$ . Linear Algebra Appl. 247, 337–345 (1996)