

## SKEW-SYMMETRIC SOLVENT FOR SOLVING A POLYNOMIAL EIGENVALUE PROBLEM

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ABSTRACT. In this paper a nonlinear matrix equation is considered which has the form

$$P(X) = A_0X^m + A_1X^{m-1} + \cdots + A_{m-1}X + A_m = 0,$$

where  $X$  is an  $n \times n$  unknown real matrix and  $A_m, A_{m-1}, \dots, A_0$  are  $n \times n$  matrices with real elements. Newton's method is applied to find the skew-symmetric solvent of the matrix polynomial  $P(X)$ . We also suggest an algorithm which converges the skew-symmetric solvent even if the Fréchet derivative of  $P(X)$  is singular.

### 1. Introduction

For solving an  $m$ -th order ordinary differential equation which has a form

$$A_0 \frac{d^m}{dt^m} x(t) + A_1 \frac{d^{m-1}}{dt^{m-1}} x(t) + \cdots + A_{m-1} \frac{d}{dt} x(t) + A_m x(t) = 0,$$

where  $A_m, A_{m-1}, \dots, A_0$  are  $n \times n$  real matrices, we need to consider the polynomial eigenvalue problem

$$(1.1) \quad P(\lambda)v = (\lambda^m A_0 + \lambda^{m-1} A_1 + \cdots + \lambda A_{m-1} + A_m)v = 0.$$

For solving the problem (1.1) we may consider the matrix equation

$$(1.2) \quad P(X) = A_0X^m + A_1X^{m-1} + \cdots + A_{m-1}X + A_m = 0.$$

If  $m = 2$  the matrix equation (1.1) can be rewritten by

$$(1.3) \quad Q(\lambda)v = (\lambda^2 A_0 + \lambda A_1 + A_2)v = 0,$$

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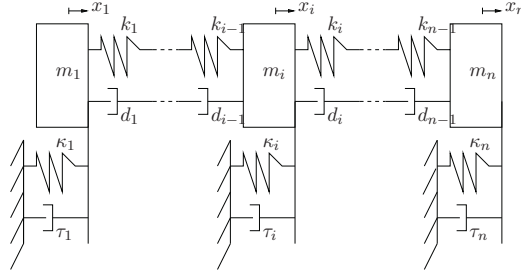


FIGURE 1. An  $n$  degree of freedom damped mass-spring system. [9]

which arise from a freedom damped mass-spring system [2]. Figure 1 shows a connected damped mass-spring system. The  $i$ -th mass of weight  $m_i$  is connected to the  $(i + 1)$ -th mass by a spring with constant  $k_i$  and damper with constant  $d_i$ , and ground by a spring with constant  $\kappa_i$  and damper constant  $\tau_i$ .

Mehrmann and Watkins [6] showed that When  $A_0 = A_0^T$ ,  $A_1 = -A_1^T$ ,  $A_2 = A_2^T$  in the quadratic eigenvalue problem (1.3), it has a Hamiltonian eigenstructure. An application of finding skew-symmetric solvent of matrix polynomial comes from the polynomial eigenvalue problem (1.1), since any skew-symmetric matrix has a pair of purely imaginary eigenvalues [4], [7]. In this paper we suggest an algorithm for solving skew-symmetric solvent of matrix polynomial.

## 2. Newton's methods for nonlinear matrix equation

From the Fréchet derivative in Newton's method of the matrix polynomial (1.2), it is necessary to find the solution  $H \in \mathbb{C}^{n \times n}$  of the equation

$$(2.1) \quad P_X(H) = \sum_{i=1}^m \left[ \left( \sum_{\mu=0}^{m-i} A_\mu X^{m-(\mu+i)} \right) H X^{i-1} \right] = -P(X).$$

REMARK 2.1. Recall that  $P_X$  is regular if and only if

$$\inf_{\|H\|=1} \|P_X(H)\| > 0.$$

Kratz and Stickel [5] used the Schur algorithm to solve (2.1). For a given  $X \in \mathbb{C}^{n \times n}$ , compute the Schur decomposition of  $X$

$$(2.2) \quad Q^* X Q = U$$

where  $Q$  is unitary and  $U$  is upper triangular. Then, substituting (2.2) into (2.1), the system is transformed to

$$(2.3) \quad \sum_{i=1}^m \left( \sum_{\mu=0}^{m-i} A_\mu X^{m-(\mu+i)} \right) H' U^{i-1} = F$$

where  $H' = H Q$  and  $F = -P(X)Q$ . Taking the vec operator both sides of (2.3) makes a linear system such that

$$(2.4) \quad \widetilde{F} \text{vec}(H') = \text{vec}(F)$$

where the matrix  $\widetilde{F} \in \mathbb{C}^{n \times n}$  is

$$(2.5) \quad \widetilde{F} = \sum_{i=1}^m \left[ (U^{i-1})^T \otimes \left( \sum_{\mu=0}^{m-i} A_\mu X^{m-(\mu+i)} \right) \right].$$

Seo and Kim [8] defined  $\widetilde{F}_{ij} = \sum_{i=1}^m [U^{i-1}]_{ji} \left( \sum_{\mu=1}^{m-i} A_\mu X^{m-(\mu+i)} \right)$  to reduce the system size of the equation (2.4) to  $n \times n$ , then  $\widetilde{F}$  in (2.5) is represented by

$$(2.6) \quad \widetilde{F} = \begin{bmatrix} \widetilde{F}_{11} & & & \\ \widetilde{F}_{21} & \widetilde{F}_{22} & & 0 \\ \vdots & \vdots & \ddots & \\ \widetilde{F}_{n1} & \widetilde{F}_{n2} & \cdots & \widetilde{F}_{nn} \end{bmatrix}.$$

If we suppose that the matrices  $\widetilde{F}_{ii}$  are nonsingular, then using the block forward substitution, the equation (2.4) can be changed to  $n$  linear systems with size  $n \times n$  such that

$$\begin{aligned} h'_1 &= \widetilde{F}_{11}^{-1} f_1 \\ h'_2 &= \widetilde{F}_{22}^{-1} (f_2 - \widetilde{F}_{21} h'_1) \\ &\vdots \\ h'_n &= \widetilde{F}_{nn}^{-1} (f_n - \widetilde{F}_{n1} h'_1 - \cdots - \widetilde{F}_{n,n-1} h'_{n-1}), \end{aligned}$$

where  $h'_i$  and  $f_i$  are the  $i$ th columns of  $H'$  and  $F$ , respectively.

**3. Skew-symmetric solvents of the matrix polynomial  $P(X)$**

Here, we consider an algorithm to compute skew-symmetric solutions of the  $q$ -th Newton iteration (2.1).

ALGORITHM 3.1.

1. *Input*  $n \times n$  real matrices  $A_0, A_1, \dots, A_m$  and skew-symmetric matrix  $X_q \in \mathbb{R}^{n \times n}$ .
2. *Choose* a skew-symmetric starting matrix  $H_{q_0} \in \mathbb{R}^{n \times n}$ .

$$3. \quad k = 0; \quad R_0 = -P(X_q) - \left( \sum_{i=1}^m \sum_{\mu=0}^{m-i} A_\mu X_q^{m-(\mu+i)} H_{q_0} X_q^{i-1} \right)$$

$$Z_0 = \sum_{i=1}^m \left( \sum_{\mu=0}^{m-i} A_\mu X_q^{m-(\mu+i)} \right)^T R_0 (X_q^{i-1})^T$$

$$P_0 = \frac{1}{2}(Z_0 - Z_0^T)$$

4. **while**  $R_k \neq 0$

$$H_{q_{k+1}} = H_{q_k} + \frac{\|R_k\|^2}{\|P_k\|^2} P_k$$

$$R_{k+1} = -P(X_q) - \left( \sum_{i=1}^m \sum_{\mu=0}^{m-i} A_\mu X_q^{m-(\mu+i)} H_{q_{k+1}} X_q^{i-1} \right)$$

$$Z_{k+1} = \sum_{i=1}^m \left( \sum_{\mu=0}^{m-i} A_\mu X_q^{m-(\mu+i)} \right)^T R_{k+1} (X_q^{i-1})^T$$

$$P_{k+1} = \frac{1}{2}(Z_{k+1} - Z_{k+1}^T) + \frac{\text{tr}(Z_{k+1} P_k)}{\|P_k\|^2} P_k.$$

**end**

REMARK 3.2. The matrices  $P_k$  and  $H_{q_k}$  are skew-symmetric in Algorithm 3.1.

By Algorithm 3.1, we can obtain some properties which are useful for the proof of our convergence theory.

LEMMA 3.3. *Let  $H_q$  be a skew-symmetric solution of the  $q$ -th Newton iteration (2.1), then*

$$(3.1) \quad \text{tr} [P_k^T (H_q - H_{q_k})] = \|R_k\|^2, \quad \text{for } k = 0, 1, \dots$$

*Proof.* When  $k = 0$ , we obtain

$$\begin{aligned}
& \operatorname{tr} [P_0^T (H_q - H_{q_0})] \\
&= \operatorname{tr} \left[ \frac{1}{2} (Z_0 - Z_0^T)^T (H_q - H_{q_0}) \right] \\
&= \operatorname{tr} [Z_0^T (H_q - H_{q_0})] \\
&= \operatorname{tr} \left\{ \left[ \sum_{i=1}^m \left( \sum_{\mu=0}^{m-i} A_\mu X_q^{m-(\mu+i)} \right)^T R_0 (X_q^{i-1})^T \right]^T (H_q - H_{q_0}) \right\} \\
&= \operatorname{tr} \left\{ R_0^T \left[ \sum_{i=1}^m \sum_{\mu=0}^{m-i} A_\mu X_q^{m-(\mu+i)} (H_q - H_{q_0}) X_q^{i-1} \right] \right\} \\
&= \operatorname{tr} \left\{ R_0^T \left[ -P(X_q) - \left( \sum_{i=1}^m \sum_{\mu=0}^{m-i} A_\mu X_q^{m-(\mu+i)} H_{q_0} X_q^{i-1} \right) \right] \right\} \\
&= \|R_0\|^2,
\end{aligned}$$

by Algorithm 3.1.

We assume that (3.1) holds for  $k = l$ , then

$$\begin{aligned}
& \operatorname{tr} [P_{l+1}^T (H_q - H_{q_{l+1}})] \\
&= \operatorname{tr} \left\{ \left[ \frac{1}{2} (Z_{l+1} - Z_{l+1}^T) + \frac{\operatorname{tr}(Z_{l+1} P_l)}{\|P_l\|^2} P_l \right]^T (H_q - H_{q_{l+1}}) \right\} \\
&= \operatorname{tr} [Z_{l+1}^T (H_q - H_{q_{l+1}})] + \frac{\operatorname{tr}(Z_{l+1} P_l)}{\|P_l\|^2} \operatorname{tr} [P_l^T (H_q - H_{q_{l+1}})] \\
&= \operatorname{tr} \left\{ \left[ \sum_{i=1}^m \left( \sum_{\mu=0}^{m-i} A_\mu X_q^{m-(\mu+i)} \right)^T R_{l+1} (X_q^{i-1})^T \right]^T (H_q - H_{q_{l+1}}) \right\} \\
&= \operatorname{tr} \left\{ R_{l+1}^T \left[ \sum_{i=1}^m \sum_{\mu=0}^{m-i} A_\mu X_q^{m-(\mu+i)} (H_q - H_{q_{l+1}}) X_q^{i-1} \right] \right\} \\
&= \operatorname{tr} \left\{ R_{l+1}^T \left[ -P(X_q) - \left( \sum_{i=1}^m \sum_{\mu=0}^{m-i} A_\mu X_q^{m-(\mu+i)} H_{q_{l+1}} X_q^{i-1} \right) \right] \right\} \\
&= \operatorname{tr} (R_{l+1}^T R_{l+1}) = \|R_{l+1}\|^2,
\end{aligned}$$

from Algorithm 3.1 and from the following result

$$\begin{aligned}
\operatorname{tr} [P_l^T (H_q - H_{q+1})] &= \operatorname{tr} \left[ P_l^T \left( H_q - H_{q_l} - \frac{\|R_l\|^2}{\|P_l\|^2} P_l \right) \right] \\
&= \operatorname{tr} [P_l^T (H_q - H_{q_l})] - \frac{\|R_l\|^2}{\|P_l\|^2} \operatorname{tr} (P_l^T P_l) \\
&= \|R_l\|^2 - \|R_l\|^2 \\
&= 0.
\end{aligned}$$

□

LEMMA 3.4. *Suppose that the  $q$ -th Newton iteration (2.1) is consistent and there exists a integer number  $l$  such that  $R_k \neq 0$  for all  $k = 0, 1, \dots, l$ . Then by Lemma 3.3  $P_k \neq 0$  and we have*

$$(3.2) \quad \operatorname{tr} (R_k^T R_j) = 0 \text{ and } \operatorname{tr} (P_k^T P_j) = 0 \quad \text{for } k > j = 0, 1, \dots, l, l \geq 1.$$

*Proof.* We prove the conclusion (3.2) using the principle induction.

i) We firstly prove  $\operatorname{tr} (R_k^T R_{k-1}) = 0$  and  $\operatorname{tr} (P_k^T P_{k-1}) = 0$  for  $k = 0, 1, \dots, l$ . When  $l = 1$ , from Algorithm 3.1

$$\begin{aligned}
&\operatorname{tr} (R_1^T R_0) \\
&= \operatorname{tr} \left\{ \left[ R_0 - \frac{\|R_0\|^2}{\|P_0\|^2} \left( \sum_{i=1}^m \sum_{\mu=0}^{m-i} A_\mu X_q^{m-(\mu+i)} P_0 X_q^{i-1} \right) \right]^T R_0 \right\} \\
&= \operatorname{tr} (R_0^T R_0) - \frac{\|R_0\|^2}{\|P_0\|^2} \operatorname{tr} \left[ \left( \sum_{i=1}^m \sum_{\mu=0}^{m-i} A_\mu X_q^{m-(\mu+i)} P_0 X_q^{i-1} \right)^T R_0 \right] \\
&= \|R_0\|^2 \\
&\quad - \frac{\|R_0\|^2}{\|P_0\|^2} \operatorname{tr} \left\{ P_0^T \left[ \sum_{i=1}^m \left( \sum_{\mu=0}^{m-i} A_\mu X_q^{m-(\mu+i)} \right)^T R_0 (X_q^{i-1})^T \right] \right\} \\
&= \|R_0\|^2 - \frac{\|R_0\|^2}{\|P_0\|^2} \operatorname{tr} (P_0^T Z_0) \\
&= \|R_0\|^2 - \frac{\|R_0\|^2}{\|P_0\|^2} \operatorname{tr} \left[ P_0^T \frac{1}{2} (Z_0 - Z_0^T) \right] \\
&= \|R_0\|^2 - \frac{\|R_0\|^2}{\|P_0\|^2} \operatorname{tr} (P_0^T P_0) \\
&= 0,
\end{aligned}$$

and

$$\begin{aligned}
\operatorname{tr}(P_1^T P_0) &= \operatorname{tr} \left\{ \left[ \frac{1}{2} (Z_1 - Z_1^T) + \frac{\operatorname{tr}(Z_1 P_0)}{\|P_0\|^2} P_0 \right]^T P_0 \right\} \\
&= \operatorname{tr}(Z_1^T P_0) + \frac{\operatorname{tr}(Z_1 P_0)}{\|P_0\|^2} \operatorname{tr}(P_0^T P_0) \\
&= \operatorname{tr}(P_0^T Z_1) + \operatorname{tr}(Z_1 P_0) \\
&= -\operatorname{tr}(Z_1 P_0) + \operatorname{tr}(Z_1 P_0) \\
&= 0.
\end{aligned}$$

If we assume that  $\operatorname{tr}(R_s^T R_{s-1}) = 0$  and  $\operatorname{tr}(P_s^T P_{s-1}) = 0$  hold for  $l = s$ , then we obtain

$$\begin{aligned}
&\operatorname{tr}(R_{s+1}^T R_s) \\
&= \operatorname{tr} \left\{ \left[ R_s - \frac{\|R_s\|^2}{\|P_s\|^2} \left( \sum_{i=1}^m \sum_{\mu=0}^{m-i} A_\mu X_q^{m-(\mu+i)} P_s X_q^{i-1} \right) \right]^T R_s \right\} \\
&= \operatorname{tr}(R_s^T R_s) - \frac{\|R_s\|^2}{\|P_s\|^2} \operatorname{tr} \left[ \left( \sum_{i=1}^m \sum_{\mu=0}^{m-i} A_\mu X_q^{m-(\mu+i)} P_s X_q^{i-1} \right)^T R_s \right] \\
&= \|R_s\|^2 \\
&\quad - \frac{\|R_s\|^2}{\|P_s\|^2} \operatorname{tr} \left\{ P_s^T \left[ \sum_{i=1}^m \left( \sum_{\mu=0}^{m-i} A_\mu X_q^{m-(\mu+i)} \right)^T R_s (X_q^{i-1})^T \right] \right\} \\
&= \|R_s\|^2 - \frac{\|R_s\|^2}{\|P_s\|^2} \operatorname{tr}(P_s^T Z_s) \\
&= \|R_s\|^2 - \frac{\|R_s\|^2}{\|P_s\|^2} \operatorname{tr} \left[ P_s^T \frac{1}{2} (Z_s - Z_s^T) \right] \\
&= \|R_s\|^2 - \frac{\|R_s\|^2}{\|P_s\|^2} \operatorname{tr} \left[ P_s^T \left( P_s - \frac{\operatorname{tr}(Z_s P_{s-1})}{\|P_{s-1}\|^2} P_{s-1} \right) \right] \\
&= \|R_s\|^2 - \|R_s\|^2 + \frac{\|R_s\|^2 \operatorname{tr}(Z_s P_{s-1})}{\|P_s\|^2 \|P_{s-1}\|^2} \operatorname{tr}(P_s^T P_{s-1}) \\
&= 0,
\end{aligned}$$

and

$$\begin{aligned}
& \operatorname{tr}(P_{s+1}^T P_s) \\
&= \operatorname{tr} \left\{ \left[ \frac{1}{2} (Z_{s+1} - Z_{s+1}^T) + \frac{\operatorname{tr}(Z_{s+1} P_s)}{\|P_s\|^2} P_s \right]^T P_s \right\} \\
&= \operatorname{tr}(Z_{s+1}^T P_s) + \frac{\operatorname{tr}(Z_{s+1} P_s)}{\|P_s\|^2} \operatorname{tr}(P_s^T P_s) \\
&= \operatorname{tr}(P_s^T Z_{s+1}) + \operatorname{tr}(Z_{s+1} P_s) \\
&= -\operatorname{tr}(Z_{s+1} P_s) + \operatorname{tr}(Z_{s+1} P_s) \\
&= 0.
\end{aligned}$$

ii) Suppose that  $\operatorname{tr}(R_s^T R_j) = 0$  and  $\operatorname{tr}(P_s^T P_j) = 0$  hold for all  $j = 0, 1, \dots, s-1$ . Then, from Algorithm 3.1 and i) we get

$$\begin{aligned}
& \operatorname{tr}(R_{s+1}^T R_j) \\
&= \operatorname{tr} \left\{ \left[ R_s - \frac{\|R_s\|^2}{\|P_s\|^2} \left( \sum_{i=1}^m \sum_{\mu=0}^{m-i} A_\mu X_q^{m-(\mu+i)} P_s X_q^{i-1} \right) \right]^T R_j \right\} \\
&= \operatorname{tr}(R_s^T R_j) - \frac{\|R_s\|^2}{\|P_s\|^2} \operatorname{tr} \left[ \left( \sum_{i=1}^m \sum_{\mu=0}^{m-i} A_\mu X_q^{m-(\mu+i)} P_s X_q^{i-1} \right)^T R_j \right] \\
&= -\frac{\|R_s\|^2}{\|P_s\|^2} \operatorname{tr} \left\{ P_s^T \left[ \sum_{i=1}^m \left( \sum_{\mu=0}^{m-i} A_\mu X_q^{m-(\mu+i)} \right)^T R_j (X_q^{i-1})^T \right] \right\} \\
&= -\frac{\|R_s\|^2}{\|P_s\|^2} \operatorname{tr}(P_s^T Z_j) \\
&= -\frac{\|R_s\|^2}{\|P_s\|^2} \operatorname{tr} \left[ P_s^T \frac{1}{2} (Z_j - Z_j^T) \right] \\
&= -\frac{\|R_s\|^2}{\|P_s\|^2} \operatorname{tr} \left[ P_s^T \left( P_j - \frac{\operatorname{tr}(Z_j P_{j-1})}{\|P_{j-1}\|^2} P_{j-1} \right) \right] \\
&= -\frac{\|R_s\|^2}{\|P_s\|^2} \operatorname{tr}(P_s^T P_j) + \frac{\|R_s\|^2 \operatorname{tr}(Z_j P_{j-1})}{\|P_s\|^2 \|P_{j-1}\|^2} \operatorname{tr}(P_s^T P_{j-1}) \\
&= 0,
\end{aligned}$$

and



$$\begin{aligned}
 & \operatorname{tr} (P_{s+1}^T P_j) \\
 &= \operatorname{tr} \left\{ \left[ \frac{1}{2} (Z_{s+1} - Z_{s+1}^T) + \frac{\operatorname{tr} (Z_{s+1} P_s)}{\|P_s\|^2} P_s \right]^T P_j \right\} \\
 &= \operatorname{tr} (Z_{s+1}^T P_j) + \frac{\operatorname{tr} (Z_{s+1} P_s)}{\|P_s\|^2} \operatorname{tr} (P_s^T P_j) \\
 &= \operatorname{tr} \left\{ \left[ \sum_{i=1}^m \left( \sum_{\mu=0}^{m-i} A_\mu X_q^{m-(\mu+i)} \right)^T R_{s+1} (X_q^{i-1})^T \right]^T P_j \right\} \\
 &= \operatorname{tr} \left[ R_{s+1}^T \left( \sum_{i=1}^m \sum_{\mu=0}^{m-i} A_\mu X_q^{m-(\mu+i)} P_j X_q^{i-1} \right) \right] \\
 &= \operatorname{tr} \left[ R_{s+1}^T \frac{\|P_j\|^2}{\|R_j\|^2} (R_j - R_{j+1}) \right] \\
 &= \frac{\|P_j\|^2}{\|R_j\|^2} \operatorname{tr} (R_{s+1}^T R_j) - \frac{\|P_j\|^2}{\|R_j\|^2} \operatorname{tr} (R_{s+1}^T R_{j+1}) \\
 &= 0,
 \end{aligned}$$

for all  $j = 0, 1, \dots, s-1$ . Hence, we complete the proof by i) and ii).  $\square$

From Lemma 3.4 we know that, if there is a positive number  $l$  such that  $R_k \neq 0$  for all  $k = 0, 1, \dots, l$ , then, the matrices  $R_k$  and  $R_j$  are orthogonal for  $k \neq j$ .

**THEOREM 3.5.** *Let the  $q$ -th Newton iteration (2.1) has a skew-symmetric solution  $H_q$ . Then for a given skew-symmetric starting matrix, the solution  $H_q$  can be found, at most, in  $n^2$  steps.*

This theorem can be proved by the similar way of Theorem 3.3 in [1].

*Proof.* From Lemma 3.4, the set  $\{R_0, R_1, \dots, R_{n^2-1}\}$  is an orthogonal basis of  $\mathbb{R}^{n \times n}$ . Since the  $q$ -th Newton iteration (2.1) has a skew-symmetric solution, and using Lemma 3.3,  $P_k \neq 0$  for  $k$ . By Algorithm 3.1 and Lemma 3.4 we obtain  $H_{q_{n^2}}$  and  $R_{n^2}$ , and  $\operatorname{tr} (R_{n^2}^T R_k) = 0$  for  $k = 0, 1, \dots, n^2 - 1$ . However,  $\operatorname{tr} (R_{n^2}^T R_k) = 0$  holds only when  $R_{n^2} = 0$ , which implies that  $H_{q_{n^2}}$  is a solution of the  $q$ -th Newton iteration. Thus  $H_{q_{n^2}}$  is a skew-symmetric matrix.  $\square$

From Newton's method and the above theorem, we have the following result.

**THEOREM 3.6.** *Suppose that the matrix polynomial has a skew-symmetric solvent and each Newton iteration is consistent for a skew-symmetric starting matrix  $X_0$ . The sequence  $\{X_k\}$  is generated by Newton's method with  $X_0$  such that*

$$\lim_{k \rightarrow \infty} X_k = S,$$

*and the matrix  $S$  satisfies  $P(S) = 0$ , then  $S$  is a skew-symmetric solvent.*

The proof of the theorem is also similar to Theorem 3.4 in [1].

*Proof.* If  $H_k$  is skew-symmetric solution of  $k$ th Newton iteration then  $(k + 1)$ th approximation matrix is

$$X_{k+1} = X_0 + H_0 + \cdots + H_k.$$

By the properties of skew-symmetric matrix  $X_{k+1}$  is also skew-symmetric. Since, the Newton sequence  $\{X_k\}$  converges to a solvent  $S$ , it is a skew-symmetric solvent.  $\square$

In this paper, we consider an iterative method for finding a skew-symmetric solution of matrix equation in (2.1). Then we incorporated the iterative method into Newton's method to compute the skew-symmetric solvent of matrix polynomial  $P(X)$  in (1.2).

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