

Rank Minimization for Sylvester Equation

Abstract

Sylvester equation is widely used in many problems in system and automatic control. In this paper, we prove that the well known Roth's similarity theorem (Roth (1952)) is a special case of a rank minimization theorem for Sylvester equation.

Keywords: Rank Minimization, Sylvester Equation

1. Introduction

The Sylvester matrix equation is widely used in system and automatic control community Dehghan (2011); Hajarian (2016); Wu (2008); Hu (2006); Roth (1952). In Dehghan (2011), Dehghan and Hajarian propose two algorithms for finding Hermitian reflexive and skew-Hermitian solutions of Sylvester matrix equations. In Hajarian (2016) Hajarian proposes a gradient based iterative method to solve the Sylvester matrix equation. In Wu (2008), Wu *et al.* solves the Sylvester matrix equation via Kronecker map. In Hu (2006), Hu and Cheng proposed a polynomial solution to the Sylvester matrix equation. Denote by $\mathbf{A} \in \mathbb{F}^{m \times m}$, $\mathbf{B} \in \mathbb{F}^{n \times n}$, and $\mathbf{C} \in \mathbb{F}^{m \times n}$ three given matrices over some field \mathbb{F} . Denote by $GL(n, \mathbb{F}) = \{\mathbf{M} \in \mathbb{F}^{n \times n} | \det \mathbf{M} \neq 0\}$ the general linear group of degree n over the field \mathbb{F} . The following theorem is the well-known Roth's similarity theorem, which provides a sufficient and necessary condition for guaranting the consistency of the Sylvester equation (1.1) in terms of an equivalence between two associated matrices.

Theorem 1.1 (Roth (1952)). *The matrix equation*

$$\mathbf{A}\mathbf{X} - \mathbf{X}\mathbf{B} = \mathbf{C} \tag{1.1}$$

is solvable w.r.t $\mathbf{X} \in \mathbb{F}^{m \times n}$ if and only if there exists a matrix $\mathbf{P} \in GL(m + n, \mathbb{F})$ such that

$$\mathbf{P} \begin{pmatrix} \mathbf{A} & \mathbf{C} \\ \mathbf{0} & \mathbf{B} \end{pmatrix} = \begin{pmatrix} \mathbf{A} & \mathbf{0} \\ \mathbf{0} & \mathbf{B} \end{pmatrix} \mathbf{P}$$

2. Main Results

We now generalize the Roth's similarity theorem to a general result based on rank minimization. The purpose of this note is to prove the following theorem.

Theorem 2.1. *Given $\mathbf{A}, \mathbf{B}, \mathbf{C}$ defined above, denote by we have*

$$\min\{\text{rank}(\mathbf{A}\mathbf{X} - \mathbf{X}\mathbf{B} - \mathbf{C}) | \mathbf{X} \in \mathbb{F}^{m \times n}\}$$

$$= \min \left\{ \text{rank} \left[\mathbf{P} \begin{pmatrix} \mathbf{A} & \mathbf{C} \\ \mathbf{0} & \mathbf{B} \end{pmatrix} - \begin{pmatrix} \mathbf{A} & \mathbf{0} \\ \mathbf{0} & \mathbf{B} \end{pmatrix} \mathbf{P} \right] | \mathbf{P} \in \text{GL}(m+n, \mathbb{F}) \right\}.$$

Proof. Denote by

$$\alpha(\mathbf{X}) = \mathbf{A}\mathbf{X} - \mathbf{X}\mathbf{B} - \mathbf{C}, \quad (2.1)$$

and

$$\beta(\mathbf{P}) = \mathbf{P} \begin{pmatrix} \mathbf{A} & \mathbf{C} \\ \mathbf{0} & \mathbf{B} \end{pmatrix} - \begin{pmatrix} \mathbf{A} & \mathbf{0} \\ \mathbf{0} & \mathbf{B} \end{pmatrix} \mathbf{P}. \quad (2.2)$$

Define

$$R_\alpha = \min \text{rank}\{\alpha(\mathbf{X}) | \mathbf{X} \in \mathbb{F}^{m \times n}\} \quad (2.3)$$

and

$$R_\beta = \min \text{rank}\{\beta(\mathbf{P}) | \mathbf{P} \in \text{GL}(m+n, \mathbb{F}).\} \quad (2.4)$$

From Tian (2002); TianMT (2000), we can obtain that

$$R_\alpha = \text{rank} \begin{pmatrix} \mathbf{A} & \mathbf{C} \\ \mathbf{0} & \mathbf{B} \end{pmatrix} - \text{rank} \begin{pmatrix} \mathbf{A} & \mathbf{0} \\ \mathbf{0} & \mathbf{B} \end{pmatrix}. \quad (2.5)$$

For $\mathbf{P} \in \text{GL}(m+n, \mathbb{F})$, we can obtain that

$$\begin{aligned} \text{rank} \beta(\mathbf{P}) &\geq \text{rank} \mathbf{P} \begin{pmatrix} \mathbf{A} & \mathbf{C} \\ \mathbf{0} & \mathbf{B} \end{pmatrix} - \text{rank} \begin{pmatrix} \mathbf{A} & \mathbf{0} \\ \mathbf{0} & \mathbf{B} \end{pmatrix} \mathbf{P} \\ &= \text{rank} \begin{pmatrix} \mathbf{A} & \mathbf{C} \\ \mathbf{0} & \mathbf{B} \end{pmatrix} - \text{rank} \begin{pmatrix} \mathbf{A} & \mathbf{0} \\ \mathbf{0} & \mathbf{B} \end{pmatrix} \\ &= R_\alpha. \end{aligned} \quad (2.6)$$

Hence, we have that $R_\beta \geq R_\alpha$. On the other hand, we denote by

$$\mathbf{P}_\mathbf{X} = \begin{pmatrix} \mathbf{I} & \mathbf{X} \\ \mathbf{0} & \mathbf{I} \end{pmatrix}, \quad (2.7)$$

then we have

$$\beta(\mathbf{P}_\mathbf{X}) = \begin{pmatrix} \mathbf{0} & -\alpha(\mathbf{X}) \\ \mathbf{0} & \mathbf{0} \end{pmatrix}. \quad (2.8)$$

Therefore,

$$R_\beta \leq \min\{\text{rank}\beta(\mathbf{P}_\mathbf{X}) | \mathbf{X} \in \mathbb{F}^{m \times n}\} = \min\{\text{rank}\alpha(\mathbf{X})\} = R_\alpha. \quad (2.9)$$

This completes the proof. \square

Reference

- Mehdi Dehghan, Masoud Hajarian, Two algorithms for finding the Hermitian reflexive and skew-Hermitian solutions of Sylvester matrix equations, *Applied Mathematics Letters*, Volume 24, Issue 4, Pages 444-449, 2011.
- Masoud Hajarian, Solving the general Sylvester discrete-time periodic matrix equations via the gradient based iterative method, *Applied Mathematics Letters*, Volume 52, Pages 87-95, 2016.
- Ai-Guo Wu, Feng Zhu, Guang-Ren Duan, Ying Zhang, Solving the generalized Sylvester matrix equation $AV+BW=EVF$ via a Kronecker map, *Applied Mathematics Letters*, Volume 21, Issue 10, Pages 1069-1073, 2008.
- Qingxi Hu, Daizhan Cheng, The polynomial solution to the Sylvester matrix equation, *Applied Mathematics Letters*, Volume 19, Issue 9, Pages 859-864, 2006.
- R. E. Roth, 'The equations $AX - BY = C$ and $AX - XB = C$ in equations', *Proc. Amer. Math. Soc.* **3**, 392-396, 1952.
- Y. Tian, 'The minimal rank of matrix expression $A - BX - YC$ ', *Missouri J. Math. Sci.* **14**, 40-48, 2002.
- Y. Tian, 'Rank equalities related to generalized inverses of matrices and their applications', Master Thesis, Montreal, Quebec, Canada, 2000.