

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

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