

On the \star -Sylvester Equation $AX \pm X^*B^* = C$

Chun-Yueh Chiang

Department of Applied Mathematics
National Chiao Tung University, Taiwan
A joint work with E. K.-W. Chu and W.-W. Lin

Oct., 20, 2008

Outline

- 1 Introduction
- 2 *-Sylvester Equation
- 3 Numerical Examples
- 4 Related Equations
- 5 Conclusions

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- In [Braden1998], the Lyapunov-like linear matrix equation

$$A^*X + X^*A = B, \quad A, X \in \mathbb{C}^{m \times n} \quad (m \neq n)$$

with $(\cdot)^* = (\cdot)^T$ was considered using generalized inverses. Applications occur in Hamiltonian mechanics.

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- In this talk, we consider the ★-Sylvester equation

$$AX \pm X^*B^* = C, \quad A, B, X \in \mathbb{C}^{n \times n}. \quad (1.1)$$

This includes the special cases of the T-Sylvester equation when $\star = T$ and the H-Sylvester equation when $\star = H$.

- Some related equations of (1.1), e.g., $AXB^* \pm X^* = C$, $AXB^* \pm CX^*D^* = E$, $AX \pm X^*A^* = C$, $AX \pm YB = C$, $AXB \pm CYD = E$, $AXA^* \pm BYB^* = C$ and $AXB \pm (AXB)^* = C$ will also be studied.

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- Our tools include the (generalized and periodic) Schur, (generalized) singular value and QR decompositions.
- An interesting application, for the *-Sylvester equation (1.1)

$$AX \pm X^*B^* = C, \quad A, B, X \in \mathbb{C}^{n \times n}$$

arises from the eigensolution of the palindromic linearization [Chu2007]

$$(\lambda Z + Z^*)x = 0, \quad Z = \begin{bmatrix} A & B \\ C & D \end{bmatrix} \in \mathbb{C}^{2n \times 2n}.$$

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Applying congruence, we have

$$\begin{bmatrix} I_n & 0 \\ X & I_n \end{bmatrix} (\lambda Z + Z^*) \begin{bmatrix} I_n & X^* \\ 0 & I_n \end{bmatrix} = \begin{bmatrix} \lambda A + A^* & \lambda(A X^* + B) + (X A + C)^* \\ \lambda(X A + C) + (A X^* + B)^* & \lambda \mathcal{R}(X) + \mathcal{R}(X)^* \end{bmatrix}$$

with

$$\mathcal{R}(X) \equiv X A X^* + X B + C X^* + D.$$

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How solve the *-Riccati equation?

$$\mathcal{R}(X) = 0.$$

- If we can solve $\mathcal{R}(X) = 0$, then the palindromic linearization can then be “square-rooted”. We then have to solve the generalized eigenvalue problem for the pencil $\lambda(AX^* + B) + (XA + C)^*$, with the reciprocal eigenvalues in $\lambda(XA + C) + (AX^* + B)^*$ obtained for free.

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- Solving the *-Riccati equation is of course as difficult as the original eigenvalue problem of $\lambda Z + Z^*$. The usual invariance/deflating subspace approach for Riccati equations leads back to the original difficult eigenvalue problem.

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- Solving the ★-Riccati equation is of course as difficult as the original eigenvalue problem of $\lambda Z + Z^*$. The usual invariance/deflating subspace approach for Riccati equations leads back to the original difficult eigenvalue problem.
- the application of Newton’s method lead to the iterative process

$$\delta X_{k+1}(AX_k^* + B) + (X_k A + C)\delta X_{k+1}^* = -\mathcal{R}(X_k)$$

which is a ★-Sylvester equation for δX_{k+1} .

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Recalled the ★-Sylvester equation (1.1)

$$AX \pm X^* B^* = C, \quad A, B, X \in \mathbb{C}^{n \times n}.$$

With the Kronecker product, (1.1) can be written as

$$\mathcal{P} \operatorname{vec}(X) = \operatorname{vec}(C), \quad \mathcal{P} \equiv I \otimes A \pm (B \otimes I)E, \quad (2.1)$$

where

$$A \otimes B \equiv [a_{ij} B] \in \mathbb{C}^{n^2 \times n^2}, \quad \operatorname{vec}(X) \equiv \begin{bmatrix} X(:, 1) \\ X(:, 2) \\ \vdots \\ X(:, n) \end{bmatrix} \in \mathbb{C}^{n^2 \times 1}.$$

And,

$$E \equiv \sum_{1 \leq i, j \leq n} e_i e_j^T \otimes e_j e_i^T, \quad e_i = \begin{bmatrix} \vdots \\ \vdots \\ 1 \\ \vdots \\ \vdots \end{bmatrix}.$$

Note that $E \operatorname{vec}(X) = \operatorname{vec}(X^T)$, $E(A \otimes B)E = B \otimes A$.

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The matrix operator on the left-hand-side of (2.1) is $n^2 \times n^2$.

- The application of Gaussian elimination and the like will be inefficient.
- The approach ignores the structure of the original problem.

Another approach will be to transform (1.1) by some unitary P and Q , so that (1.1) becomes:

- For $\star = T$:

$$PAQ \cdot \overline{Q}^T X P^T \pm P X^T \overline{Q} \cdot Q^T B^T P^T = PCP^T. \quad (2.2)$$

Let $(Q^H A^H P^H, Q^H B^H P^H)$ be in (upper-triangular) generalized Schur form.

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- For $\star = H$:

$$PAQ \cdot Q^H X P^H \pm P X^H Q \cdot Q^H B^H P^H = P C P^H. \quad (2.3)$$

Let $(Q^H A^H P^H, Q^H B^H P^H)$ be in (upper-triangular) generalized Schur form.

The transformed equations in (2.2) and (2.3) then have the form

$$\begin{bmatrix} a_{11} & 0^T \\ a_{21} & A_{22} \end{bmatrix} \begin{bmatrix} x_{11} & x_{12}^* \\ x_{21} & X_{22} \end{bmatrix} \pm \begin{bmatrix} x_{11}^* & x_{21}^* \\ x_{12} & X_{22}^* \end{bmatrix} \begin{bmatrix} b_{11}^* & b_{21}^* \\ 0 & B_{22}^* \end{bmatrix} \quad (2.4)$$

$$= \begin{bmatrix} c_{11} & c_{12}^* \\ c_{21} & C_{22} \end{bmatrix}.$$

Multiply the matrices out, we have

$$a_{11}x_{11} \pm b_{11}^*x_{11}^* = c_{11}, \quad (2.5)$$

$$a_{11}x_{12}^* \pm x_{21}^*B_{22}^* = c_{12}^* \mp x_{11}^*b_{21}^*, \quad (2.6)$$

$$A_{22}x_{21} \pm b_{11}^*x_{12} = c_{21} - x_{11}a_{21}, \quad (2.7)$$

$$A_{22}X_{22} \pm X_{22}^*B_{22}^* = \tilde{C}_{22} \equiv C_{22} - a_{21}x_{12}^* \mp x_{12}b_{21}^*. \quad (2.8)$$

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From (2.5) for $\star = T$, we have

$$(a_{11} \pm b_{11})x_{11} = c_{11}. \quad (2.9)$$

Let $\lambda_1 \equiv a_{11}/b_{11} \in \sigma(A, B)$. The solvability condition of the above equation is

$$a_{11} \pm b_{11} \neq 0 \Leftrightarrow \lambda_1 \neq \mp 1. \quad (2.10)$$

From (2.5) when $\star = H$, we have

$$a_{11}x_{11} \pm \bar{b}_{11}\bar{x}_{11} = c_{11}. \quad (2.11)$$

To solve (2.11) is to write it together with its complex conjugate in the composite form

$$\begin{bmatrix} a_{11} & \pm b_{11}^* \\ \pm b_{11} & a_{11}^* \end{bmatrix} \begin{bmatrix} x_{11} \\ x_{11}^* \end{bmatrix} = \begin{bmatrix} c_{11} \\ c_{11}^* \end{bmatrix}.$$

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The determinant of the matrix operator in above:

$$d = |a_{11}|^2 - |b_{11}|^2 \neq 0 \Leftrightarrow |\lambda_{11}| \neq 1. \quad (2.12)$$

requiring that no eigenvalue $\lambda \in \sigma(A, B)$ lies on the unit circle.

From (2.6) and (2.7), we obtain

$$\begin{bmatrix} a_{11}^* I & \pm B_{22} \\ \pm b_{11}^* I & A_{22} \end{bmatrix} \begin{bmatrix} x_{12} \\ x_{21} \end{bmatrix} = \begin{bmatrix} \tilde{c}_{12} \\ \tilde{c}_{21} \end{bmatrix} \equiv \begin{bmatrix} c_{12} \\ c_{21} \end{bmatrix} + x_{11} \begin{bmatrix} \mp b_{21} \\ -a_{21} \end{bmatrix}. \quad (2.13)$$

With $a_{11} = b_{11} = 0$, x_{11} will be undetermined. However, $\sigma(A, B) = \mathbb{C}$ and this case will be excluded by (2.16).

- If $a_{11} \neq 0$, (2.13) is then equivalent to

$$\begin{bmatrix} a_{11}^* I & \pm B_{22} \\ 0 & A_{22} - \frac{b_{11}^*}{a_{11}^*} B_{22} \end{bmatrix} \begin{bmatrix} x_{12} \\ x_{21} \end{bmatrix} = \begin{bmatrix} \tilde{c}_{12} \\ \tilde{c}_{21} \end{bmatrix} \equiv \begin{bmatrix} \tilde{c}_{12} \\ \tilde{c}_{21} \mp \frac{b_{11}^*}{a_{11}^*} \tilde{c}_{12} \end{bmatrix}. \quad (2.14)$$

The solvability condition of (2.13) and (2.14) is

$$\det \tilde{A}_{22} \neq 0, \quad \tilde{A}_{22} \equiv A_{22} - \frac{b_{11}^*}{a_{11}^*} B_{22}$$

or that λ and λ^{-*} cannot be in $\sigma(A, B)$ together. Note that \tilde{A}_{22} is still lower-triangular, just like A or B .

- If $b_{11} \neq 0$, (2.13) is equivalent to

$$\begin{bmatrix} 0 & B_{22} - \frac{a_{11}^*}{b_{11}^*} A_{22} \\ b_{11}^* I & \pm A_{22} \end{bmatrix} \begin{bmatrix} x_{12} \\ x_{21} \end{bmatrix} = \begin{bmatrix} \hat{c}_{12} \\ \pm \tilde{c}_{21} \end{bmatrix} \equiv \begin{bmatrix} \pm \tilde{c}_{12} - \frac{a_{11}^*}{b_{11}^*} \tilde{c}_{21} \\ \pm \tilde{c}_{21} \end{bmatrix} \quad (2.15)$$

with an identical solvability condition (2.16). Lastly, (2.8) is of the same form as (1.1) but of smaller size.

We summarize the solvability condition for (1.1) in the following theorem:

Theorem 1

The *-Sylvester equation (1.1):

$$AX \pm X^* B^* = C, \quad A, B \in \mathbb{C}^{n \times n}$$

is uniquely solvable if and only if the condition:

$$\lambda \in \sigma(A, B) \Rightarrow \lambda^{-\star} \notin \sigma(A, B) \quad (2.16)$$

is satisfied. Here, the convention that 0 and ∞ are mutually reciprocal is followed.

The process in this subsection is summarized below: (with BS denoting back-substitution)

Algorithm SSylvester

(For the unique solution of $AX \pm X^{\star}B^{\star} = C$; $A, B, C, X \in \mathbb{C}^{n \times n}$.)

- Compute the lower-triangular generalized Schur form (PAQ, PBQ) using QZ.
- Store (PAQ, PBQ, PCP^{\star}) in (A, B, C) .
- Solve (2.9) for $\star = T$, or (2.11) for $\star = H$; if fail, exit.

If $n = 1$ or $|a_{11}|^2 + |b_{11}|^2 \leq \text{tolerance}$, exit.

If $|a_{11}| \geq |b_{11}|$, then

if $\tilde{A}_{22} \equiv A_{22} - \frac{b_{11}^*}{a_{11}^*} B_{22}$ has any negligible diagonal elements, then exit.

Else if $\tilde{B}_{22} \equiv B_{22} - \frac{a_{11}^*}{b_{11}^*} A_{22}$ has any negligible diagonal elements, then exit.

Else compute $x_{21} = \tilde{B}_{22}^{-1} \hat{c}_{12}$ by BS, $x_{12} = (\pm \tilde{c}_{21} \mp A_{22} x_{21}) / b_{11}^*$ (c.f. (2.15)).

- Apply **Algorithm TSylvester** to $A_{22} X_{22} \pm X_{22}^* B_{22}^* = \tilde{C}_{22}$, $n \leftarrow n - 1$.
- Output $X \leftarrow QX\bar{P}$ for $\star = T$, or $X \leftarrow QXP$ for $\star = H$.

End of algorithm

Cost

Let the operation count of the Algorithm SSylvester be $f(n)$ complex flops, we assume that A, B are lower-triangular matrices. (After a QZ procedure ($66n^3$))

- Inverting $\tilde{A}_{22} \equiv A_{22} - \frac{b_{11}^*}{a_{11}^*} B_{22}$ or $\tilde{B}_{22} \equiv B_{22} - \frac{a_{11}^*}{b_{11}^*} A_{22}$ ($\frac{1}{2}n^2$ flops).
- Computing $x_{21} = \tilde{B}_{22}^{-1} \hat{c}_{12}$ and $x_{12} = (\pm \tilde{c}_{21} \mp A_{22} x_{21}) / b_{11}^*$ (n^2 flops).
- Forming $\tilde{C}_{22} = C_{22} - a_{21} x_{12}^* \mp x_{12} a_{21}^*$ ($2n^2$).

Thus $f(n) \approx f(n-1) + \frac{7}{2}n^2$, ignoring $O(n)$ terms. This implies that $f(n) \approx \frac{7}{6}n^3$ and the total operation count for Algorithm SSylvester is $67\frac{1}{6}n^3$ complex flops, ignoring $O(n^2)$ terms.

Solvability Condition

- The solvability condition of

$$AX \pm X^*B^* = C$$

is obviously identical to that of

$$\mathcal{P} \operatorname{vec}(X) = \operatorname{vec}(C), \quad \mathcal{P} = I \otimes A \pm (B \otimes I)E.$$

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However, E reshuffles the columns of $B \otimes I$, making the analysis of the matrix operator \mathcal{P} difficult.

- Consider the trivial example when $n = 2$, $A = [a_{ij}]$ and $B = [b_{ij}]$ are lower-triangle matrices, we have

$$\mathcal{P} = \begin{bmatrix} a_{11} \pm b_{11}^* & & & & \\ \pm b_{21}^* & a_{11} & & \pm b_{22}^* & \\ a_{21} & \pm b_{11}^* & a_{22} & & \\ & a_{21} \pm b_{21}^* & & a_{22} & \\ & & & & \end{bmatrix}.$$

The eigenvalues of the corresponding $\tilde{\mathcal{P}}$ are $\lambda_{ii} = a_{ii} \pm b_{ij}^*$ ($i = 1, 2$) and those of the middle block W_{12} where

$$W_{ij} \equiv \begin{bmatrix} a_{ii} & \pm b_{ij}^* \\ \pm b_{ii}^* & a_{jj} \end{bmatrix}.$$

The characteristic polynomial of W_{ij} , identical to that for W_{ji} , is $\lambda^2 - (a_{ii} + a_{jj})\lambda + \det W_{ij}$ with $\det W_{ij} = a_{ii}a_{jj} - b_{ii}^*b_{ij}^*$, and the eigenvalues are

$$\lambda_{W_{ij}} = \frac{1}{2} \left[a_{ii} + a_{jj} \pm \sqrt{(a_{ii} - a_{jj})^2 + 4b_{ii}^*b_{ij}^*} \right].$$

Note that some λ_{ii} or $\lambda_{W_{ij}} = 0$ if and only if (2.16) in Theorem 1 is violated.

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Example1

- In MATLAB commands: $\hat{A} = \text{tril}(\text{randn}(n), -1) + \text{diag}(a)$, $\hat{B} = \text{tril}(\text{randn}(n), -1) + \text{diag}(b)$ and $C = \text{randn}(n)$, where $a, b \in \mathbb{R}^n$.
- To guarantee condition (2.16), let $b = \text{randn}(n, 1)$, $a = 2b$. In Table1, we list the CPU time ratios, corresponding residuals and their ratios, with increasing dimensions $n = 16, 25, 30, 35, 40$.
- Note that the operation counts for the SSA and KRP methods are approximately $67n^3$ and $\frac{2}{3}n^6$ flops respectively (the latter for the LU decomposition of the $n^2 \times n^2$ matrix in (2.1)).

Table1: Results for Example1

n	$\frac{t_{KRP}}{t_{ASS}}$	Res(ASS)	Res(KRP)	$\frac{\text{Res(KRP)}}{\text{Res(ASS)}}$
16	1.00e+00	1.8527e-17	2.1490e-17	1.16
25	1.31e+01	2.3065e-17	2.8686e-17	1.24
30	2.61e+01	3.1126e-18	5.7367e-18	2.20
35	6.48e+01	7.0992e-18	1.2392e-17	1.75
40	1.05e+02	1.7654e-18	6.4930e-18	3.68

- The results in Table1 show that the advantage of ASS over KRP in CPU time grows rapidly as n increases, as predicted by the operation counts.

- The results in Table1 show that the advantage of ASS over KRP in CPU time grows rapidly as n increases, as predicted by the operation counts.
- Even with better management of sparsity or parallelism, the $O(n^6)$ operation count makes the KRP approach uncompetitive even for moderate size n . The residuals from ASS is also better than that from KRP, as (2.1) is solved by Gaussian elimination in an unstructured way.

Example2

- We let $a = [\alpha + \epsilon, \beta]^\top$, $b = [\beta, \alpha]^\top$, where α, β are two randomly numbers greater than 1, with the spectral set $\sigma(A, B) = \{\frac{\alpha+\epsilon}{\beta}, \frac{\beta}{\alpha}\}$, and $|\lambda_1\lambda_2 - 1| = \frac{\epsilon}{\alpha}$. Judging from (2.16), (1.1) has worsening condition when ϵ decreases.
- We report a comparison of absolute residuals for the ASS and KRP approaches for $\epsilon = 10^{-1}, 10^{-3}, 10^{-5}, 10^{-7}$ and 10^{-9} in Table2.
- The results show that if (2.1) is solved by Guassian elimination, its residual will be larger than that for ASS especially for smaller ϵ . Note that the size of X reflects partially the condition of (1.1). The KRP approach copes less well than the ASS approach for an ill-conditioned problem.

Table2: Results for Example2

ϵ	Res(ASS)	Res(KRP)	$\frac{\text{Res(KRP)}}{\text{Res(ASS)}}$	$O(\ X\)$
1.0e-1	2.0673e-15	2.4547e-15	1.19	10^1
1.0e-3	8.6726e-13	4.3279e-13	0.50	10^3
1.0e-5	2.3447e-12	2.4063e-12	1.03	10^3
1.0e-7	5.9628e-10	1.1786e-09	1.98	10^6
1.0e-9	5.8632e-08	3.4069e-07	5.81	10^8

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Generalized *-Sylvester equation I

The more general version of the *-Sylvester equation I:

$$AXB^* \pm X^* = C$$

with $A, B^*, X^* \in \mathbb{C}^{m \times n}$ is uniquely solvable if and only if the condition:

$$\lambda \in \sigma(AB) \Rightarrow \lambda^{-*} \notin \sigma(AB)$$

is satisfied.

Generalized *-Sylvester equation II

The more general version of the *-Sylvester equation II:

$$AXB^* \pm CX^*D^* = E$$

is uniquely solvable if and only if the condition:

$$\lambda_1, \lambda_2 \in \sigma(A, C); \lambda_3, \lambda_4 \in \sigma(D, B) \Rightarrow \lambda_1\lambda_2 \neq \lambda_3\lambda_4$$

is satisfied.

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- We have considered the solution of the ★-Sylvester equation which has not been fully investigated before. The solvability conditions have been derived and algorithms have been proposed.
- It is interesting and exciting that the ★ above the second X in (1.1) makes the equation behave very differently.
 1. For the ordinary continuous-time Sylvester equation $AX \pm XB = C$, the solvability condition is: $\sigma(A) \cap \sigma(\mp B) = \emptyset$.
 2. For the ordinary discrete-time Sylvester equation $X \pm AXB = C$, the the solvability condition is: if $\lambda \in \sigma(A)$, then $\mp \lambda^{-1} \notin \sigma(B)$.

(1.1) looks like a Sylvester equation associated with continuous-time but (2.16) is satisfied when $\sigma(A, B)$ is totally inside the unit circle, hinting at a discrete-time type of stability behaviour.

Thank you for your attention!