

# Convergence analysis of a Riccati-based stabilization method

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## Abstract

In this paper we discuss the convergence of a stabilization algorithm based on a singular version of the Discrete Riccati Difference Equation. This method is particularly appealing for large scale linear time invariant dynamical systems since its complexity can nicely exploit the sparsity of such systems.

## 1 Introduction

In this paper, we focus on the stabilization of a discrete-time system

$$x_{i+1} = Ax_i + Bu_i, \quad (1)$$

where  $A$  and  $B$  are  $n \times n$  and  $n \times p$  real matrices which are known, and  $x_i$  and  $u_i$  are vectors of dimension  $n$  and  $p$  respectively. The stabilization of the system requires the computation of a  $p \times n$  feedback matrix  $F$  such that all eigenvalues of  $A - BF$  are inside the unit circle and therefore the system defined by replacing  $A$  with  $A - BF$  is stable. For small and moderate values of  $n$ ,  $F$  can be computed via pole placement or the solution of a matrix

equation, e.g., Riccati or Lyapunov equations. The computational requirements for standard algorithms for these approaches, however, is prohibitive for large values of  $n$ . Fortunately, when  $n$  is large and  $p \ll n$ , the system matrix  $A$  and/or input matrix  $B$  are typically very sparse. Algorithms for such problems must therefore exploit this structure in order to efficiently compute a stabilizing feedback.

## 2 Saad's Approach

An important contribution to solving large scale stabilization problems with a few unstable eigenvalues is Y. Saad's projection method [7]. In this algorithm, stabilization or eigenvalue assignment is only imposed on a small invariant subspace that contains the unstable invariant subspace of  $A$ . Such an approach is often effective, but it can have convergence difficulties and the need for a basis of the invariant subspace can cause excess space requirements for very large systems.

In Saad's projection method, a left invariant subspace  $V^T$  of  $A$  (with presumably small dimension), that contains the left unstable invariant subspace of  $A$  is computed. In order to exploit the possible sparsity of the matrix  $A$  one often chooses to compute the basis directly by a subspace iteration like method. The low-order projected system  $(V^T A V, V^T B)$  is then stabilized and the reduced feedback  $F_u$  is lifted back to form a stabilizing feedback  $F = F_u V^T$  of the original system  $(A, B)$ . Subspace iteration like methods as proposed by Saad, generate a sequence of approximations to a particular invariant subspace  $V$  starting from an initial subspace  $V_0$ . The convergence of such methods depends on the separation between eigenvalues of  $A$  "contained" in  $V$  and the eigenvalues of  $A$  not "contained" in  $V$ . This is the so-called *gap* of  $A$  with respect to  $V$  and if it is too small, one should try to compute a larger space instead (see [6]).

In this paper, we discuss an efficient alternative that addresses this convergence difficulty. We also prove that this algorithm converges under very mild conditions and we show that it avoids the need for an explicitly formed basis of the invariant subspace.

### 3 Discrete Riccati Equation Stabilization

The major results of this paper are based on the discrete-time Riccati equation (DRE) and the discrete-time Riccati difference equation (DRDE)

$$P = A^T(P - PB(R + B^T P B)^{-1} B^T P)A + Q \quad (2)$$

$$P_{i+1} = A^T(P_i - P_i B(R + B^T P_i B)^{-1} B^T P_i)A + Q \quad (3)$$

where  $R$  and  $Q$  are  $p \times p$  and  $n \times n$  non-negative matrices and  $Q$  is usually decomposed into  $L_Q L_Q^T$ . The most general results about DRE and DRDE convergence are given in [2]. It is shown there that under the condition of stabilizability of  $(A, B)$ , a stabilizer and non-negative solution  $P_s$  of DRE (2) exists and a stabilizing feedback  $F$  can be computed by

$$F \doteq \hat{R}^{-1} B^T P_s A, \quad \hat{R} \doteq (R + B^T P_s B).$$

Whether the solution of DRDE (3) converges to the stabilizing solution of DRE depends on properties of  $(A^T, L_Q)$  and the initial condition  $P_0$ . We establish in this paper that this algorithm converges to the stabilizing solution under more general conditions than those reported in [2].

### 4 Basic properties of the DRDE

The Riccati difference equation (3) has several equivalent formulations. First, one can rewrite it as the Schur complement (with respect to the (1,1) block) of the compound matrix

$$M = \begin{bmatrix} R + B^T P_i B & B^T P_i A \\ A^T P_i B & A^T P_i A + Q \end{bmatrix}. \quad (4)$$

From this one easily derives a factorized form of the algorithm [4]. One needs to assume that the Cholesky factorizations of the positive semi-definite matrices  $R$ ,  $Q$  and  $P_i$  are given :

$$R \doteq L_R L_R^T, \quad Q \doteq L_Q L_Q^T, \quad P_i \doteq S_i S_i^T. \quad (5)$$

Using these one obtains trivially the following non-square factorization of  $M$  :

$$M = \begin{bmatrix} L_R & B^T S_i & 0 \\ 0 & A^T S_i & L_Q \end{bmatrix} \cdot \begin{bmatrix} L_R^T & 0 \\ S_i^T B & S_i^T A \\ 0 & L_Q^T \end{bmatrix}. \quad (6)$$

The so-called square root form of the Riccati difference iteration is then obtained from a lower triangular reduction of the left factor ([4]) :

$$\begin{bmatrix} L_R & B^T S_i & 0 \\ 0 & A^T S_i & L_Q \end{bmatrix} \cdot U_i = \begin{bmatrix} \hat{L}_i & 0 & 0 \\ \hat{K}_i & S_{i+1} & 0 \end{bmatrix} \quad (7)$$

where  $U_i$  is orthogonal. We will assume in this paper that  $R > 0$ , which implies that  $\hat{R}_i \doteq R + B P_i B^T > 0$  as well. As a consequence, we obtain a decomposition of  $M$  :

$$M = \begin{bmatrix} \hat{L}_i & 0 \\ \hat{K}_i & S_{i+1} \end{bmatrix} \cdot \begin{bmatrix} \hat{L}_i^T & \hat{K}_i^T \\ 0 & S_{i+1}^T \end{bmatrix}, \quad (8)$$

from which it follows that the Schur complement with respect to the (1,1) block equals  $P_{i+1} = S_{i+1} \cdot S_{i+1}^T$ . Notice that this holds even if  $P_{i+1}$  is not of full rank.

Another formulation of (3) follows from the underlying two-point boundary value problem [8, 1] :

$$\begin{bmatrix} A & 0 \\ -Q & I_n \end{bmatrix} \begin{bmatrix} X_{i+1} \\ Y_{i+1} \end{bmatrix} = \begin{bmatrix} I_n & B R^{-1} B^T \\ 0 & A^T \end{bmatrix} \begin{bmatrix} X_i \\ Y_i \end{bmatrix},$$

where  $P_i = Y_i X_i^{-1}$  implies  $P_i = Y_{i+1} X_{i+1}^{-1}$  and vice versa (this implies of course that both  $X_i$  and  $X_{i+1}$  must be invertible). We rederive this formulation below in a more explicit form.

### Lemma 1

If  $R > 0$  the DRDE (3) can be rewritten as follows

$$\begin{bmatrix} A & 0 \\ -Q & I_n \end{bmatrix} \begin{bmatrix} I_n \\ P_{i+1} \end{bmatrix} = \begin{bmatrix} I_n & B R^{-1} B^T \\ 0 & A^T \end{bmatrix} \begin{bmatrix} I_n \\ P_i \end{bmatrix} A_{F_i}, \quad (9)$$

where

$$A_{F_i} \doteq A - B \cdot F_i, \quad F_i \doteq \hat{R}_i^{-1} B^T P_i A, \quad \hat{R}_i \doteq R + B^T P_i B.$$

**Proof :** We need to show the following two identities

$$A = (I + B R^{-1} B^T P_i) A_{F_i}, \quad P_{i-1} - Q = A^T P_i A_{F_i}.$$

Using the definition of the matrices involved, the second equation becomes

$$\begin{aligned} P_{i+1} &= A^T P_i A - A^T P_i B F_i + Q \\ &= A^T P_i A - A^T P_i B \hat{R}_i^{-1} B^T P_i A + Q, \end{aligned}$$

which is the DRDE. The first equation becomes

$$A = A + B R^{-1} B^T P_i A - B F_i - B R^{-1} B^T P_i B F_i$$

which is equivalent to

$$0 = B[R^{-1} \hat{R}_i - I - R^{-1} B^T P_i B] F_i$$

and is clearly an identity. ■

## 5 Convergence of the DRDE

If one wants to study the convergence of the DRDE, the above lemma plays a crucial role. It is clear from (9) that the generalized eigenvalue problem

$$\lambda M_1 - M_2 \doteq \lambda \begin{bmatrix} A & 0 \\ -Q & I_n \end{bmatrix} - \begin{bmatrix} I_n & B R^{-1} B^T \\ 0 & A^T \end{bmatrix}$$

will determine the convergence of the DRDE. For simplicity we assume  $A$  to be invertible here but it can be shown that this assumption does not affect our results. Iteration (9) is then a subspace iteration with a space of dimension  $n$  :

$$\begin{bmatrix} X_{i+1} \\ Y_{i+1} \end{bmatrix} = M_1^{-1} M_2 \begin{bmatrix} X_i \\ Y_i \end{bmatrix}.$$

Let  $\lambda_i$  be an eigenvalue of  $M_1^{-1} M_2$  and assume they are ordered by decreasing magnitude  $|\lambda_i|$ . If  $|\lambda_n|$  is strictly larger than  $|\lambda_{n+1}|$  then the above recurrence is known to converge for almost all initial conditions  $X_0, Y_0$ , to the so-called dominant invariant subspace of  $M_1^{-1} M_2$ . If, on the other hand,  $|\lambda_n| = |\lambda_{n+1}|$  then the iteration almost never converges : there exist fixed points but they correspond to very special initial conditions [3]. It turns out that  $M_1^{-1} M_2$  is symplectic and therefore has a special eigenvalue pattern : the eigenvalues which are not on the unit circle come in pairs that are mirror images of each

other with respect to the unit circle. Therefore the condition  $|\lambda_n| > |\lambda_{n+1}|$  is satisfied iff  $M_1^{-1}M_2$  has no eigenvalues on the unit circle. We make this assumption in the rest of the paper. This is a classical assumption in the RDE literature since it is closely linked to the existence of stabilizing solutions of the corresponding feedback problem [2]. We recall in this context the following results proved in [2].

**Theorem 2**

*A stabilizing solution  $P_s$  of the DRE exists and is unique if and only if either of the following two conditions is satisfied*

1.  *$(A, B)$  is stabilizable and  $(A^T, Q)$  has no unobservable eigenvalues on the unit circle,*
2.  *$(A, B)$  is stabilizable and the pencil  $\lambda M_1 - M_2$  has no generalized eigenvalues on the unit circle.*

The symplectic structure of the pencil implies that all eigenvalues are then mirror images of each other with respect to the unit circle, and the following result then holds ([2, 3]).

**Theorem 3**

*Let the symplectic pencil  $\lambda M_1 - M_2$  have no generalized eigenvalues on the unit circle. Then there exist invertible matrices  $S$  and  $T$  such that*

$$(\lambda M_1 - M_2)S = T \begin{bmatrix} \lambda A_F - I & 0 \\ 0 & \lambda I - A_F^T \end{bmatrix},$$

where  $A_F$  is stable and depends on the stabilizing solution  $P_s$  as follows :

$$A_F \doteq A - B \cdot F, \quad F \doteq \hat{R}^{-1} B^T P_s A, \quad \hat{R} \doteq R + B^T P_s B.$$

Under these conditions, the power method thus converges, provided the initial matrix  $\begin{bmatrix} X_0 \\ Y_0 \end{bmatrix}$  has a “non-degenerate” component in the direction of the invariant subspace  $\begin{bmatrix} I_n \\ P_s \end{bmatrix}$ . When expressing the initial matrix as a linear combination of both invariant spaces (spanned by the block columns of  $S$ ) :

$$\begin{bmatrix} X_0 \\ Y_0 \end{bmatrix} = S \begin{bmatrix} V \\ W \end{bmatrix},$$

the non-degeneracy implies that  $V$  must be invertible. Since

$$V = \begin{bmatrix} I_n & 0_n \end{bmatrix} S^{-1} \begin{bmatrix} X_0 \\ Y_0 \end{bmatrix}, \quad (10)$$

it is easy to see that for random initial matrices  $X_0$  and  $Y_0$  the matrix  $V$  is generically invertible. The DRDE thus almost always converges to the stabilizing solution of the RDE the corresponding symplectic pencil  $\lambda M_1 - M_2$  has no unit circle eigenvalues.

#### Theorem 4

*Let the symplectic pencil  $\lambda M_1 - M_2$  have no generalized eigenvalues on the unit circle and let the initial matrix  $P_0 \doteq Y_0 X_0^{-1}$  satisfy the non-degeneracy condition (10). Then the iterates  $P_i \doteq Y_i X_i^{-1}$  converge linearly to the stabilizing solution  $P_s$  of the RDE :*

$$\lim_{i \rightarrow \infty} P_i = P_s, \quad \lim_{i \rightarrow \infty} \|P_{i+1} - P_s\| / \|P_i - P_s\| = c < 1.$$

## 6 Convergence to $P_s$

We already know that the invariant subspace computed at each iteration  $i$  converges to the stable invariant subspace we are interested in, but one typically wants to know this in terms of the matrix  $P_i$  as well. Although it is normal to expect linear convergence here as well, we analyze this in more detail in this section.

The following simple lemma follows by straightforward error analysis of the inverse of a matrix and can be found in slightly modified form in [9].

**Lemma 5** Let  $A$  be a square invertible matrix with smallest singular value  $\sigma_{min}$  and let  $E$  be a perturbation of norm smaller than this :

$$\|E\|_2 \doteq \delta < \sigma_{min}.$$

Then

$$\begin{aligned} (A + E)^{-1} &= A^{-1} - A^{-1} E A^{-1} + \Delta \\ \Delta &= (A + E)^{-1} E A^{-1} E A^{-1} = A^{-1} E A^{-1} E (A + E)^{-1}, \\ \|\Delta\|_2 &\approx \|A^{-1} E A^{-1} E A^{-1}\|_2 < \delta^2 / \sigma_{min}^3. \end{aligned}$$

Defining the convergence error as follows

$$E_i \doteq P_i - P_s,$$

and applying the above lemma to the expressions

$$\hat{R}_i^{-1} = (R + B^T P_i B)^{-1},$$

$$P_{i+1} = A^T [P_i - P_i B \hat{R}_i^{-1} B^T P_i] A + Q,$$

we obtain

$$\hat{R}_i^{-1} = \hat{R}_i^{-1} - \hat{R}_i^{-1} B^T E_i B \hat{R}_i^{-1} + O(\|E_i\|_2^2)$$

and

$$\begin{aligned} P_{i+1} &= A^T [E_i - E_i B \hat{R}_i^{-1} B^T P_i - P_i B \hat{R}_i^{-1} B^T E_i \\ &\quad + P_i B \hat{R}_i^{-1} B^T E_i B \hat{R}_i^{-1} B^T P_i] A + O(\|E_i\|_2^2), \\ &= (A - B F_i)^T E_i (A - B F_i) + O(\|E_i\|_2^2), \end{aligned}$$

where  $F_i \doteq \hat{R}_i^{-1} B^T P_i A$ .

**Corollary 6** Let  $A_{F_i}$  be the closed loop matrix  $A + B F_i$  and let the error  $E_i \doteq P_i - P_s$  between the  $i$ -th iterate of the DRDE and its steady state value  $P_s$  be small, then this error converges linearly and is in first order equal to

$$E_{i+1} = A_{F_i}^T E_i A_{F_i} + O(\|E_i\|_2^2).$$

## 7 The singular SQR algorithm

The square root algorithm (SQR) of this paper is based on the DRDE with  $Q = 0$ . In the previous section we showed that the DRDE equation converges under very mild conditions to the stabilizing solution provided the corresponding pencil  $\lambda M_1 - M_2$  has no unit circle eigenvalues. For  $Q = 0$  this pencil has a spectrum that is the union of the spectrum of  $A$  and that of  $A^{-1}$  since

$$\lambda M_1 - M_2 = \lambda \begin{bmatrix} A & 0 \\ 0 & I_n \end{bmatrix} - \begin{bmatrix} I_n & B R^{-1} B^T \\ 0 & A^T \end{bmatrix}.$$



Therefore the feedback  $F$  generated in the limit moves the unstable eigenvalues of  $A$ ,  $\lambda$  to their unit circle mirror images,  $1/\bar{\lambda}$ , and leaves the stable eigenvalues unchanged. As a special case of the square root form of DRDE, the SQR stabilization algorithm (developed in [6]) has the form

$$\begin{bmatrix} L_R & B^T S_i \\ 0 & A^T S_i \end{bmatrix} U_i = \begin{bmatrix} \hat{L}_i & 0 \\ \hat{K}_i & S_{i+1} \end{bmatrix} \quad (11)$$

where  $U_i$  is orthogonal and the dimension of  $S_i$  is  $n \times l$ , the same as  $S_0$ . Note that the QR decomposition is computed for a small matrix with size  $(p+l) \times p$  (the first row of (7)) and feedback  $F_i$  can be computed from  $\hat{L}_i$  and  $\hat{K}_i$ . Moreover, if  $A$  and  $B$  are sparse, the construction of the left factor in the left hand side of (11) is cheap as well (see [6]).

The SQR iteration can produce the same sequence of subspaces as Saad's subspace iteration method with only an additional economical QR decomposition of  $S_i$  since the updating of  $S_i$  has the form  $S_{i+1} = A^T S_i U_i^{22}$ . If  $S_0$  is taken to be the same initial subspace basis as used for Saad's method, SQR will converge. Moreover convergence is easier to check as was pointed out in [6].

It is also useful to point out that for  $Q = 0$  the DRDE can be rewritten in a very compact manner :

$$P_{i+1} = A^T P_i A_{F_i},$$

or equivalently

$$S_{i+1} S_{i+1}^T = A^T S_i S_i^T A_{F_i}. \quad (12)$$

In the limit we also have that  $P_s$  satisfies the discrete-time Sylvester equation

$$P_s = A^T P_s A_F.$$

## 8 Comparing Saad's method and SQR

Saad's subspace iteration method essentially performs the  $QR$  factorization of  $A^T V_i$  where  $V_i$  is the previously computed orthogonal base :

$$A^T V_i = V_{i+1} R_{i+1}. \quad (13)$$

Comparing this with

$$A^T S_i U_i^{22} = S_{i+1}, \quad (14)$$

it is obvious that both methods compute the same spaces. Because of (13,14),

$$\text{Im} V_0 = \text{Im} S_0 \implies \text{Im} V_i = \text{Im} S_i \quad \forall i,$$

as long as  $U_i^{22}$  and  $R_{i+1}$  are invertible. Multiplying (12) by the right inverse of  $S_{i+1}^T$  we obtain :

$$U_i^{22} = S_i^T A_{F_i} S_{i+1}^+.$$

Upon convergence,  $S_{i+1}$  and  $S_i$  are close to each other, and one shows that  $S_i^T A_{F_i} S_{i+1}^+$  is then a matrix whose spectrum is a subset of that of  $A_{F_i}$  and hence is stable. The effect of such a multiplication is to dampen out the components along the smallest eigenvalues of  $S_i^T A_{F_i} S_{i+1}^+$ , and the iterates  $S_i$  may converge to a smaller rank matrix. This is actually what happens in practice if  $S_0$  has dimension larger than the number of unstable eigenvalues of  $A$ .

In order to analyze this we put ourselves in a special coordinate system, where

$$A = \begin{bmatrix} A_{11} & 0 \\ A_{21} & A_{22} \end{bmatrix},$$

where  $A_{11}$  is unstable and  $A_{22}$  is stable.

**Theorem 7** *Let  $A$  be in the coordinate system described above. Then the solution to the DRE has rank equal to the dimension of the unstable subspace of  $A$ . The invariant subspace satisfies*

$$\begin{bmatrix} A_{11} & 0 & 0 & 0 \\ A_{21} & A_{22} & 0 & 0 \\ 0 & 0 & I & 0 \\ 0 & 0 & 0 & I \end{bmatrix} \begin{bmatrix} I & 0 \\ 0 & I \\ P_{11} & 0 \\ 0 & 0 \end{bmatrix} =$$

$$\begin{bmatrix} I & 0 & W_{11} & W_{12} \\ 0 & I & W_{21} & W_{22} \\ 0 & 0 & A_{11}^T & A_{21}^T \\ 0 & 0 & 0 & A_{22}^T \end{bmatrix} \begin{bmatrix} I & 0 \\ 0 & I \\ P_{11} & 0 \\ 0 & 0 \end{bmatrix} A_F,$$

where

$$\begin{bmatrix} W_{11} & W_{12} \\ W_{21} & W_{22} \end{bmatrix} \doteq \begin{bmatrix} B_1 \\ B_2 \end{bmatrix} R^{-1} \begin{bmatrix} B_1^T & B_2^T \end{bmatrix}.$$

The matrix  $P_s$  in this coordinate system is given by

$$P_s \doteq \begin{bmatrix} P_{11} & 0 \\ 0 & 0 \end{bmatrix}$$

and has rank equal to the number of unstable eigenvalues of  $A$ .

**Proof :** This can be shown using the property that  $A_{22}$  is already stable and solving a RDE of smaller dimension :

$$P_{11} = A_{11}^T (P_{11} - P_{11} B_1 (R + B_1^T P_{11} B_1) B_1^T P_{11}) A_{11},$$

to stabilize the smaller system. ■

This theorem implies that the image of  $P_s$  is also the desired unstable left invariant subspace of  $A$ , which explains that when  $S_0$  has rank larger than the number of unstable eigenvalues of  $A$ , some components of  $S_i$  have to be damped out in the iteration. When we overestimate the dimension of the unstable invariant subspace, we therefore nevertheless converge to a subspace of correct dimension. Moreover, Corollary 6 implies that the spectrum of  $A_F$  determines the convergence ratio of  $P_i$  towards the stabilizing solution  $P_s$ . Convergence will occur provided the initial matrix  $P_0$  satisfies the non-degeneracy condition (10). A test for checking whether convergence has occurred was presented in [6], where several numerical experiments are also reported.

## 9 Conclusion

The results of this paper give a theoretical explanation of the convergence behaviour observed in [6]. The analysis also give a proof that the DRDE converges to a stabilizing solution of the DRE under milder conditions than those of [2], provided an asymptotically stabilizing solution exists.

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