DEVELOPMENT OF A NUMERICAL ALGORITHM FOR UNCOUPLING CONSTANT COEFFICIENT STATE EQUATIONS OF CONTROL THEORY

A Dissertation

Presented to

the Faculty of the Department of Electrical Engineering University of Houston

> In Partial Fulfillment of the Requirements for the Degree Doctor of Philosophy

> > by Kyung Sik Yoo May 1974

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ABSTRACT

A new uncoupling algorithm for system differential equations based on the matrix sign function is presented in this paper. Special forms of system equations arising in many classes of system optimization are investigated. The set of n differential equations formed by the states and costates are uncoupled requiring only the integration of one matrix differential equations of the order n/2. Among the special forms considered are the stiff state equations with constant coefficients for which a numerical algorithm is presented. The algorithm groups the system eigenvalues into separated subsets and generates completely uncoupled filter matrices. Several example solutions are developed using the new method to illustrate the outlined procedures and the numerical accuracy.

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CHAPTER I

INTRODUCTION

Considerable research has been carried out in the problem areas of optimal linear quadratic control and optimal filtering [2]. The two main theoretical approaches to the solution of a control optimization problem have been Bellman's maximum principle, which is based on the principle of optimality, and Pontryagin's minimum principle, which is an extension of the classical calculus of variations [3,7]. The minimum principle was originally developed for continuous-time problems and recently has been extended to discrete-time problems [32].

The application of the minimum principle of Pontryagin to the optimal control problem results in a numerical solution of the "two-point boundary value problem." The computational procedure for solving the linear two-point boundary value problems has been the subject of many recent technical reports. The most common technique for the solution of linear optimal control developed to date deals with the algebraic Riccati equation generated from a canonical set of system equations [20,23].

In addition, the appearance of Riccati equations in the optimal linear filter with Gaussian randomness has been reported in many papers. The solution matrix for the error covariance Riccati equation governs all the behavior and contains the necessary information for characterizing the optimal filter [9,21, 29,30,39].

The theorem of duality has proved that the error

covariance equation in optimal estimation is closely related to the Riccati equation for an optimal gain in the linear guadratic optimal control [19]. The integration of Riccati equations instead of the basic form of the state transition approach has been favored because of the improved stability properties [15,31,34, 381. The two most widely-used techniques for solving the Riccati equation are the direct numerical integration and the automatic synthesis program (ASP) matrix integration procedure [22]. Several papers have shown the matrix Riccati equation from an algebraic point of view and determined the asymptotic or steady-state solution to the equation [27,28,33]. The results are applied to the spectral factorization of a class of matrices arising in filtering theory and network synthesis [1,28]. A few additional papers have been devoted to the determination of the algebraic expression for the solution of the matrix Riccati equation without iterative procedures [44,45].

During the past year, the matrix sign function has been introduced as an efficient tool in the computation of eigenvalues and eigenvectors for a square matrix and in the asymptotic solution of an algebraic Riccati equation [4,5,6]. A new uncoupling algorithm for system differential equations based on the matrix sign function is presented in this paper. Special forms of system equations arising in many classes of system optimization are investigated. Among the special forms considered are the stiff state equations with constant coefficients for which a numerical algorithm is presented. The purpose of this study is twofold:

- To develop a new uncoupling algorithm to solve a set of differential or difference equations appearing in optimal control and filtering
- To present a matrix filter algorithm for integration of system equations with constant coefficients whose eigenvalues are widely spaced

In the development of the second purpose of this study (i.e., to present a new matrix filter algorithm for the integration of system equations with constant coefficients whose eigenvalues are widely spaced), the eigenvalues of the considered matrix are isolated into subsets in which each eigenvalue has the same requisite characteristic, such as the same sign or the same order of magnitude. For the systems with widely spaced eigenvalues, the conventional explicit integration methods may require excessively small integration steps.

Numerical integration techniques suitable for the solution of stiff state equations have appeared in the literature over the past decade [40,43]. One stability concept that is widely used in connection with stiff systems, called A-stability, was introduced early by Dahlquist [12]. Lawson [25] has reported on an example of the A-stable Runge Kutta method which is termed the generalized Runge-Kutta process. Rosenbrook [37] and Calahan [10] have described the implicit Runge-Kutta methods which are similar in many respects to Lawson's and are implicitly analogous to the conventional process.

Certaine [11] has considered the problem of devising a predictor-corrector method for stiff ordinary differential equa-

tions. Gear [17,18] devised a practical automatic integration routine based on Adam's predictor-corrector algorithm. Recently, Klopfensten, et al,[24] developed an algorithm, called PECE, consisting of a predictor-corrector associated with iterations of a pseudo Newton-Raphson method.

Outside the realm of direct consideration in this study is the work of Richards, et al, [36] who reported on an explicit method for large stiff systems associated with the qualitative picture of the solution paths (the direction of eigenvectors corresponding to dominant eigenvalues). A more systematic method, a second-order exact multistep method, for large systems has been developed by Fowler and Waten [16].

Somewhat related to the study developed in this paper is an important area often more limited by the "stiffness" phenomenon in the numerical determination of the transient response of electrical circuits [35,41,42]. Branin [8] has used the eigenvalue method to compute the frequency and time response of the circuit. More closely related to this study is the work of Richard, et al, [35] who proposed a procedure for removing the stiffness of the equations themselves during the course of The state variable corresponding to the largest the solution. pole has been discarded whenever the steady-state excitation of a linear network reach the time constant to that pole. A similar approach by Davison [13,14] is based on finding the dominant poles and zeros of the system and then determining the time solution in terms of those poles and zeros. Also interested in this problem is Lee [26] who has reported a more practical pro-

cedure to integrate such linear time-invariant system equations by means of a conventional matrix filter theory. He proposed that both a low-pass and a high-pass filter be constructed, and that these filters then be used to uncouple the system equations into two sets, a set with large eigenvalues and one with small eigenvalues. The development herein is related to his work.

Numerical techniques in the optimization of a linear quadratic system and the Kalman filter are reviewed in Chapter I along with a brief historical background. In addition, certain recent theoretical developments in the area of numerical integration techniques for stiff ordinary differential equations are presented.

New algorithms are developed in Chapter II to uncouple the particular forms of system matrices arising in many important classes of optimal control and estimation problems. Examples using the new algorithm in both time domains, continuous and discrete, are presented. Particular emphasis is placed on developing a new technique that groups the system eigenvalues into separated subsets and generates completely uncoupled filter matrices.

Chapter III includes an outline of existing methods for the solution of a continuous-time linear regulator with quadratic criteria. A new computational procedure is then developed using the uncoupling algorithm. This new procedure employs a forwarding integration scheme and does not require the storage of feedback gains for a complete solution.

In Chapter IV, the uncoupling algorithm is extended to

the discrete time case, and uncoupled discrete linear system equations are studied. The application of the algorithm to solve a discrete regulator problem is shown, along with a discussion of the variance equation for the Kalman filter. The derivation of a non-recursive expression for a solution matrix of a discrete Riccati equation is included.

Chapter V discusses an integration procedure for a linear stiff equation derived from the numerical determination of the transient response of electrical circuits. The merits of the band-pass filter matrix are demonstrated.

Chapter VI concludes with remarks concerning the use of the method discussed in this paper and suggestions for possible further study.

Each chapter contains example solutions using the new method to illustrate the outlined procedures and the numerical accuracy. The mathematical concept of the matrix sign function and the derivation of the steady-state solution of the matrix Riccati equation will be presented in the Appendices.

CHAPTER II

DEVELOPMENT OF ALGORITHMS

2.1 Generation of the Transformation Matrix

A recently developed similarity transformation matrix [4,5] has been constructed from a matrix sign function, and, as will be shown, reduces a matrix to a block diagonal form under proper operations.

In the generation of the matrix, if \overline{A} is of the order $n \times n$ and ℓ eigenvalues have positive real parts while m eigenvalues have negative real parts so that $\ell + m = N$, then the matrix sign function sign (\overline{A}) is obtained by

sign
$$(\overline{A}) = \begin{bmatrix} M_{11} & M_{12} \\ M_{21} & M_{22} \end{bmatrix} \begin{bmatrix} I_{\ell \times \ell} & 0 \\ 0 & -I_{m \times m} \end{bmatrix} \begin{bmatrix} M_{11} & M_{12} \\ M_{21} & M_{22} \end{bmatrix}^{-1}$$

$$(2.1)$$

where M_{ij} are partitions of the eigenvector matrix M and $I_{l \times l}$ is an $l \times l$ identity matrix. The dimensions are then compatible for matrix operations. A transformation matrix V of the order n×n can now be defined as follows:

$$V = \text{sign} (\overline{A}) + K$$
 (2.2)

where K is the matrix of $\pm I$ in the diagonal form shown in (2.1). The matrix K can be formed by computing the trace of sign \overline{A} .

Substituting (2.1) into (2.2) and using simple matrix operations,

$$\mathbf{V} = \begin{bmatrix} \mathbf{M}_{11} & \mathbf{M}_{12} \\ \mathbf{M}_{21} & \mathbf{M}_{22} \end{bmatrix} \begin{bmatrix} \mathbf{I}_{2 \times 2} & \mathbf{0} \\ \mathbf{0} & -\mathbf{I}_{m \times m} \end{bmatrix} \begin{bmatrix} \mathbf{M}_{11} & \mathbf{M}_{12} \\ \mathbf{M}_{21} & \mathbf{M}_{22} \end{bmatrix}^{-1}$$

$$+ \begin{bmatrix} I_{\ell \times \ell} & 0 \\ 0 & -I_{m \times m} \end{bmatrix} \begin{bmatrix} M_{11} & M_{12} \\ M_{21} & M_{22} \end{bmatrix} \begin{bmatrix} M_{11} & M_{12} \\ M_{21} & M_{22} \end{bmatrix}^{-1}$$
(2.2a)

which gives

$$V = \begin{bmatrix} M_{11} & -M_{12} \\ M_{21} & -M_{22} \end{bmatrix} + \begin{bmatrix} M_{11} & M_{12} \\ -M_{21} & -M_{22} \end{bmatrix} \begin{bmatrix} M_{11} & M_{12} \\ M_{21} & M_{22} \end{bmatrix}^{-1}$$
$$= 2 \begin{bmatrix} M_{11} & 0 \\ 0 & -M_{22} \end{bmatrix} \begin{bmatrix} M_{11} & M_{12} \\ M_{21} & M_{22} \end{bmatrix}^{-1}$$
(2.2b)

Matrix V in (2.2b) is the general form of the transformation matrix and may be applied to any particular form of square matrix to obtain a block diagonal form.

2.2 <u>Block Diagonal Form of a General Square Matrix</u> A square matrix A is assumed where

$$\overline{A} = \begin{bmatrix} M_{11} & M_{12} \\ M_{21} & M_{22} \end{bmatrix} \begin{bmatrix} J_1 & 0 \\ 0 & J_2 \end{bmatrix} \begin{bmatrix} M_{11} & M_{12} \\ M_{21} & M_{22} \end{bmatrix}^{-1} = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix} (2.3)$$

In this development, the submatrices J_1 and J_2 are Jordan blocks or are made up of the eigenvalues of \overline{A} .

The matrix in (2.2b) is then used to perform a similarity transformation on \overline{A} to find a new matrix \overline{A}_1 as follows:

$$\overline{A}_{1} = V^{-1}\overline{A}V = M \begin{bmatrix} M_{11}^{-1} & 0 \\ 0 & -M_{22}^{-1} \end{bmatrix} \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix} \begin{bmatrix} M_{11} & 0 \\ 0 & -M_{22} \end{bmatrix} M^{-1}$$
(2.4)

$$= \begin{bmatrix} A_{11}M_{11}S_{11} - A_{12}M_{22}S_{21} - M_{12}M_{22}^{-1}A_{21}M_{11}S_{11} + M_{12}M_{22}^{-1}A_{22}M_{22}S_{21} \\ M_{21}M_{11}^{-1}A_{11}M_{11}S_{11} - M_{21}M_{11}^{-1}A_{12}M_{22}S_{21} - A_{21}M_{11}S_{11} + A_{22}M_{22}S_{21} \\ A_{11}M_{11}S_{12}^{-A_{12}M_{22}S_{22}} - M_{12}M_{22}^{-1}A_{21}M_{11}S_{12} - M_{12}M_{22}^{-1}A_{22}M_{22}S_{22} \\ M_{21}M_{11}^{-1}A_{11}M_{11}S_{12}^{-M}A_{21}M_{11}^{-1}A_{12}M_{22}S_{22}^{-A}A_{21}M_{11}S_{12}^{-A}A_{22}M_{22}S_{22} \\ \end{bmatrix}$$

$$(2.4a)$$

In the above development, the submatrices of M^{-1} , S_{ij} are given by

$$\begin{bmatrix} s_{11} & s_{12} \\ s_{21} & s_{22} \end{bmatrix} = M^{-1} = \begin{bmatrix} (M_{11} - M_{12}M_{22}^{-1}M_{21})^{-1} & (M_{21} - M_{22}M_{12}^{-1}M_{11})^{-1} \\ (M_{12} - M_{11}M_{21}^{-1}M_{22})^{-1} & (M_{22} - M_{21}M_{11}^{-1}M_{12})^{-1} \end{bmatrix}$$
(2.4b)

In considering the (1.2) and (2.1) submatrices of (2.4a), the (2.1) submatrix is zero, as shown below:

$$M_{21}M_{11}^{-1}A_{11}M_{11}(M_{11}^{-M}M_{12}^{-1}M_{22}^{-1}M_{21}^{-1}-M_{21}M_{11}^{-1}A_{12}M_{22}(M_{12}^{-M}M_{11}^{-1}M_{21}^{-1}M_{22})^{-1}$$

$$= A_{21}M_{11}(M_{11}^{-M}M_{12}^{-1}M_{22}^{-1}M_{21}^{-1})^{-1}+A_{22}M_{22}(M_{12}^{-M}M_{11}^{-1}M_{21}^{-1}M_{22})^{-1}$$

$$= (M_{21}M_{11}^{-1}A_{11}^{+}M_{21}M_{11}^{-1}A_{12}^{-M}M_{11}^{-1}-A_{21}^{-}A_{22}^{-}M_{21}M_{11}^{-1})$$

$$\cdot (I-M_{12}M_{22}^{-1}M_{21}^{-1}M_{11}^{-1})^{-1} = 0 \qquad (2.5)$$

since the bracketed term is the asymptotic solution to the Riccati equation. The (1.2) submatrix is also zero since the bracketed term in (2.5a) below is an asymptotic solution to the matrix Riccati equation. (see Appendix)

Rearranging these terms and using the definition of J_1 and J_2 (2.3), it can be shown that the submatrices along the diagonal are as given below:

block (1.1) =
$$(M_{11} - M_{12} M_{21}^{-1} M_{21}) J_1 (M_{11} - M_{12} M_{22}^{-1} M_{21})^{-1}$$
 (2.5b)

block (2.2) =
$$(M_{22} - M_{21} M_{11}^{-1} M_{12}) J_2 (M_{22} - M_{21} M_{11}^{-1} M_{12})^{-1}$$
 (2.5c)

The matrix A1 is then of the form

$$\overline{A}_{1} = \begin{bmatrix} \overline{A}_{11} & 0 \\ 0 & \overline{A}_{22} \end{bmatrix} = \begin{bmatrix} (M_{11} - M_{12}M_{22}M_{21})J_{1}(M_{11} - M_{12}M_{22}M_{21})^{-1} & 0 \\ 0 & (M_{22} - M_{21}M_{11}M_{12}) & J_{2}(M_{22} - M_{21}M_{11}M_{12})^{-1} \end{bmatrix}$$
(2.6)

which breaks \overline{A} into submatrices of a block diagonal lower order so that the eigenvalues of \overline{A}_1 are the same as those of \overline{A} .

On the other hand, it can be shown that the similarity transformation $V\overline{A}V^{-1}$ gives a different block diagonal form.

$$V\overline{A}V^{-1} = \begin{bmatrix} M_{11} & 0 \\ 0 & -M_{22} \end{bmatrix} M^{-1} A M \begin{bmatrix} M_{11}^{-1} & 0 \\ 0 & -M_{22}^{-1} \end{bmatrix}$$

(2.7)

From Equation (2.3),

$$V\overline{A}V^{-1} = \begin{bmatrix} M_{11} & 0 \\ 0 & -M_{22} \end{bmatrix} \begin{bmatrix} J_1 & 0 \\ 0 & J_2 \end{bmatrix} \begin{bmatrix} M_{11}^{-1} & 0 \\ 0 & -M_{22}^{-1} \end{bmatrix}$$
$$= \begin{bmatrix} M_{11}J_1M_{11}^{-1} & 0 \\ 0 & M_{22}J_2M_{22}^{-1} \end{bmatrix}$$
(2.7a)

Thus, either $\sqrt{\sqrt{1}A}$ or $\sqrt{A}\sqrt{\sqrt{1}}$ may be used for the block diagonalization of \overline{A} .

2.3 Continuous Linear Systems

As will be discussed in Chapter III, a solution is required for a two-point boundary-value problem. This problem is encountered in the optimization of linear control with a quadratic performance index and a nonlinear Riccati equation for the optimal estimation of a continuous Kalman filter. In both cases, a system matrix is formed in a partitioned square matrix given by (2.8).

$$H_{CR} = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix}$$
(2.8)

The elements of A_{ij} are the coefficient matrices of the system equations and have these properties in common: $A_{11} = -A_{22}^T$, $A_{12} = A_{12}^T$, and $A_{21} = A_{21}^T$. The matrix H_{CR} is of the order thus, the submatrices are of the order $n/2 \times n/2$.

The transformation matrix V may be written by the substitution of (2.4b) into (2.2b) as follows:

$$V = 2 \begin{bmatrix} S & -T_2 S^{-1} \\ T_1 S & -S^T \end{bmatrix}$$
(2.9)

where $T_1 = M_{21}M_{11}^{-1}$, $T_2 = M_{12}M_{22}^{-1}$ and $S = (I-T_2T_1)^{-1}$.

The first column of (2.9) is postmultiplied by S^{-1} to construct a new transformation matrix. The transformation matrix \overline{V} for the uncoupling of continuous systems is developed as follows:

$$\overline{\mathbf{v}} = 2 \begin{bmatrix} \mathbf{I} & -\mathbf{T}_2 \mathbf{S}^{\mathrm{T}} \\ \mathbf{T}_1 & -\mathbf{S}^{\mathrm{T}} \end{bmatrix}$$
(2.9a)

where the inverse of \overline{V} is

$$\overline{\mathbf{v}}^{-1} = \frac{1}{2} \begin{bmatrix} \mathbf{S} & -\mathbf{ST}_2 \\ \mathbf{T}_1 & -\mathbf{I} \end{bmatrix}$$
(2.9b)

 V_1 is the desired transformation matrix for the block diagonalization process of the system matrix given by (2.8). If a similarity transformation is performed on H_{CR} by \overline{V} , then

$$\overline{H}_{CR} = \overline{v}^{-1} H_{CR} \overline{v} = \begin{bmatrix} S & -ST_2 \\ T_1 & -I \end{bmatrix} \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix} \begin{bmatrix} I & -T_2 S^T \\ T_1 & -S^T \end{bmatrix}$$
$$= \begin{bmatrix} S (A_{11}^{-T} 2^A 21^{+A} 12^T 1^{-T} 2^A 22^T 1) \\ T_1 A_{11}^{-A} 21^{+T} 1^A 12^T 1^{-A} 22^T 1 \\ -S (A_{11}^T 2^{-T} 2^A 21^T 2^{+A} 12^{-T} 2^A 22) S^T \\ (-T_1 A_{11}^T 2^{+A} 21^T 2^{-T} 1^A 12^{+A} 22) S^T \end{bmatrix}$$
(2.10)

since T₁ and T₂ are the asymptotic solutions to the matrix Riccati

equations, the (1.2) and (2.1) subblocks are zero. The details on asymptotic solutions of Riccati equations will be discussed in Chapters III and IV.

 \overline{H}_{CR} now becomes an uncoupled form

$$\overline{H}_{CR} = \begin{bmatrix} H_{C1} & 0 \\ 0 & H_{C2} \end{bmatrix}$$
(2.10a)

and taking the transpose of subblock H_{C2} yields

$$H_{C2}^{T} = S(-T_{2}^{T}A_{11}^{T}T_{1}^{T}+T_{2}^{T}A_{21}^{T}-A_{12}^{T}T_{1}^{T}+A_{22}^{T})$$
(2.10b)

In considering that $A_{11} = -A_{22}^{T}$, $A_{12} = A_{12}^{T}$, $A_{21} = A_{21}^{T}$, $T_{1} = T_{1}^{T}$ and $T_{2} = T_{2}^{T}$, a relation is obtained between submatrices H_{C1} and H_{C2} so that $H_{C1} = -H_{C2}^{T}$. This particular form of H_{CR} appears in the solution of various optimal controls and estimation problems.

A considerable reduction in computational efforts may be obtained by the use of the new transformation matrix given by (2.9a), since the resulting submatrices are of the order $n/2 \times n/2$ rather than $n \times n$. The computational procedures of an uncoupling algorithm for a continuous linear system are summarized in the following steps:

- a) Obtain the state and costate differential equations and construct H_{CP} .
- b) Compute the sign function matrix of H_{CR} and construct the transformation matrices V and \overline{V} in (2.9) and (2.9a).

c) Apply a similarity transformation to the system matrix ${\rm H}_{\rm CR}$ by $\overline{\rm V}.$

2.4 Discrete Linear Systems

The canonical difference equations obtained for the optimization of linear discrete systems can be interpreted as either forward or backward integration schemes. As will be shown in Chapter IV, the corresponding system matrices for both cases are

$$H_{DR}(\text{forward}) = \begin{bmatrix} \phi + BR^{-1}B^{T}\phi^{-T}Q & -BR^{-1}B^{T}\phi^{-T} \\ & & \\ -\phi^{-T}Q & \phi^{-T} \end{bmatrix}$$
(2.11)

and

$$H_{DR}(backward) = \begin{bmatrix} \phi^{-1} & \phi^{-1}BR^{-1}B^{T} \\ & & \\ Q\phi^{-1} & \phi^{T}+Q\phi^{-1}BR^{-1}B^{T} \end{bmatrix}$$
(2.11a)

where H_{DR} denotes the system matrix of a discrete regulator.

The dual nature of optimal estimation problems and optimal regulator problems provides equivalent relations between coefficient matrices of both systems. The system matrix for the forward canonical equations for the optimal filter will have the following general form:

$$H_{DF}(\text{forward}) = \begin{bmatrix} \phi^{-T} & \phi^{-T} H^{T} R^{-1} H \\ BQB^{T} \phi^{-T} & \phi^{+} BQB^{T} \phi^{-1} H^{T} R^{-1} H \end{bmatrix}$$
(2.11b)

The sign algorithm is useful for computing the block diagonalization form of the discrete forms. Since the sign al-

gorithm separates the eigenvalues by the sign of the real parts, the discrete canonical matrix must be mapped into the continuous domain. The bilinear transformation known in sampled data theory may be considered as

$$Z = \frac{1+S}{1-S}$$
(2.12)

where ω is a complex variable; that is, $S = \sigma + j\omega$.

The transformation in (2.12) maps the interior of the unit circle in the Z-plane onto the left half of the ω -plane. Similarly, the bilinear transformation given by (2.12a) also maps the inside of the Z-plane unit circle into the left half of the ω -plane.

$$Z = \frac{S+1}{S-1}$$
 (2.12a)

Either transformation will convert the original characteristic equation in Z into a quotient of the polynomial in S of the same order. Therefore, the domain transformation can be interpreted in terms of system eigenvalues in both planes.

Using either (2.12) or (2.12a),

$$\Lambda_{\rm C} = (\Lambda_{\rm D}^{-1}) (\Lambda_{\rm D}^{+1})^{-1}$$
 (2.13)

where Λ_D and Λ_C denote the Jordan forms of the system matrix in the discrete and complex planes, respectively. In solving (2.13) for Λ_D , the following is obtained:

$$\Lambda_{\rm D} = (1 - \Lambda_{\rm C})^{-1} (1 + \frac{1}{C})$$
 (2.13a)

It has been shown that the eigenvalues of H_{DR} and H_{DF} given by (2.10) through (2.10a) occur in reciprocal pairs so that for an eigenvalue λ_i , there exists an eigenvalue $\lambda_j = \frac{1}{\lambda_i}$ [45]. In other words, one half of the eigenvalues of the discrete system matrix lies inside the unit circle in discrete domain, while the other half lies outside. Hence, Λ_D can be written in two diagonal blocks as

$$\Lambda_{\rm D} = \begin{bmatrix} \Lambda_{\rm D1} & 0\\ 0 & \Lambda_{\rm D1}^{-1} \end{bmatrix}$$
(2.14)

Substituting (2.14) into (2.13) yields

$$\Lambda_{\mathbf{C}} = \begin{bmatrix} \Lambda_{\mathbf{D}\mathbf{1}}^{-\mathbf{I}} & \mathbf{0} \\ \mathbf{0} & \Lambda_{\mathbf{D}\mathbf{1}}^{-\mathbf{I}} \end{bmatrix} \begin{bmatrix} \Lambda_{\mathbf{D}\mathbf{1}}^{+\mathbf{I}} & \mathbf{0} \\ \mathbf{0} & \Lambda_{\mathbf{D}\mathbf{1}}^{-\mathbf{I}} \end{bmatrix}$$
(2.15)

which is

$$\Lambda_{\rm C} = \begin{bmatrix} \Lambda_{\rm Cl} & 0 \\ 0 & \Lambda_{\rm C2} \end{bmatrix} = \begin{bmatrix} (\Lambda_{\rm Dl}^{-1}) (\Lambda_{\rm Dl}^{+1})^{-1} \\ 0 & -(\Lambda_{\rm Dl}^{-1}) (\Lambda_{\rm Dl}^{+1})^{-1} \end{bmatrix}$$
(2.15a)

From (2.15a), it can be concluded that the eigenvalues of a discrete system matrix are transformed in such a manner that $\Lambda_{\rm C1} = -\Lambda_{\rm C2}.$

If M is the eigenvector matrix of the discrete system matrix and both sides of (2.13a) are multiplied by M and M^{-1} ,

$$H_{DR} = M\Lambda_{D}M^{-1} = M(I-\Lambda_{C})^{-1}(I+\Lambda_{C})M^{-1}$$
(2.16)

Then solving (2.16) for the term $H_{CR} = M \Lambda_C M^{-1}$ gives

$$H_{CR} = M\Lambda_{C}M^{-1} = (H_{DR}^{+1})^{-1}(H_{DR}^{-1})$$
 (2.17)

where H_{CR} denotes a new system matrix transformed into the complex plane whose eigenvalues are symmetric about the imaginary axis.

The matrix sign function for H_{CR} is defined by

sign H_{CR} =
$$\begin{bmatrix} M_{11} & M_{12} \\ M_{21} & M_{22} \end{bmatrix} \begin{bmatrix} I & 0 \\ 0 & -I \end{bmatrix} \begin{bmatrix} M_{11} & M_{12} \\ M_{21} & M_{22} \end{bmatrix}^{-1}$$
(2.18)

and the transformation matrix V is obtained as follows:

$$V = \operatorname{sign} H_{CR} + \begin{bmatrix} I & 0 \\ 0 & -I \end{bmatrix} = 2 \begin{bmatrix} S & -T_2 S^{T} \\ T_1 S & -S^{T} \end{bmatrix}$$
(2.19)

where $T_1 = M_{21}M_{11}^{-1}$, $T_2 = M_{12}M_{22}^{-1}$ and $S = (I-T_2T_1)^{-1}$.

Again, an alternated form of matrix \overline{V} may be reconstructed by postmultiplying the first column of V by S⁻¹. The desired transformation matrix in the complex plane is

$$\overline{V} = 2 \begin{bmatrix} I & -T_2 S^T \\ & \\ T_1 & -S^T \end{bmatrix}$$
(2.19a)

The uncoupling procedure for the new system after transformation is straightforward, using the same algorithm developed in previous sections. If \overline{H}_{CR} is the block diagonalized form of H_{CR} , and the subblocks are

$$\overline{H}_{CR} = \overline{V}^{-1} H_{CR} \overline{V} = \begin{bmatrix} H_{C1} & 0 \\ 0 & H_{C2} \end{bmatrix}$$
(2.20)

then H_{C1} and H_{C2} have the same dimensions since I and -I in (2.18) are in the same order. From (2.20) H_{CR} in terms of \overline{H}_{CR} is

$$H_{CR} = \overline{V} \,\overline{H}_{CR} \overline{V}^{-1} \tag{2.21}$$

Substituting (2.21) for (2.17) results in

$$H_{DR} = [I - \overline{V} \ \overline{H}_{CR} \overline{V}^{-1}]^{-1} [I + \overline{V} \ \overline{H}_{CR} \overline{V}^{-1}]$$
(2.22)

from which

$$H_{DR} = \overline{V} \overline{H}_{DR} \overline{V}^{-1} = \overline{V} \begin{bmatrix} H_{D1} & 0 \\ 0 & H_{D2} \end{bmatrix} \overline{V}^{-1}$$
(2.22a)

where

$$\vec{H}_{DR} = [I - \vec{H}_{CR}]^{-1} [I + \vec{H}_{CR}]$$

$$= \begin{bmatrix} (I - H_{C1})^{-1} (I + H_{C1}) & 0 \\ 0 & (I - H_{C2})^{-1} (I + H_{C2}) \end{bmatrix} (2.22b)$$

The block diagonalization of the discrete system matrix is completed by applying a similarity transformation directly to H_{DR} ; i.e.,

$$\overline{H}_{DR} = \overline{V}^{-1} H_{DR} \overline{V}$$
 (2.22c)

The system matrix for the discrete optimal filter given by (2.11a) is chosen to investigate the relation between subblocks H_{D1} and H_{D2} . From (2.11a) and (2.19a), \overline{H}_{DR} becomes

$$\begin{split} \vec{H}_{DR} &= \vec{\nabla}^{-1} H_{DR} \vec{\nabla} = \begin{bmatrix} H_{D1} & 0 \\ 0 & H_{D2} \end{bmatrix} = \begin{bmatrix} S & -ST_2 \\ T_1 & -1 \end{bmatrix} \begin{bmatrix} \phi^{-1} & \phi^{-1} BR^{-1} B^T \\ Q\phi^{-1} & \phi^T + Q\phi^{-1} BR^{-1} B^T \\ Q\phi^{-1} & \phi^T + Q\phi^{-1} BR^{-1} B^T \\ T_1 & -S^T \end{bmatrix} \\ &= \begin{bmatrix} S (\phi^{-1} - T_2 Q\phi^{-1} + \phi^{-1} BR^{-1} B^T T_1 - T_2 \phi^T T_1 - T_2 Q\phi^{-1} BR^{-1} B^T T_1) \\ T_1 \phi^{-1} - Q\phi^{-1} + T_1 \phi^{-1} BR^{-1} B^T T_1 - \phi^T T_1 - Q\phi^{-1} BR^{-1} B^T T_1 \\ S (\phi^{-1} T_2^{-T_2} Q\phi^{-1} T_2^{+\phi^{-1} BR^{-1} B^T} - T_2 \phi^T - T_2 Q\phi^{-1} BR^{-1} B^T) S^T \end{bmatrix} \end{split}$$

$$(T_{1}\phi^{-1}T_{2}-Q\phi^{-1}T_{2}+T_{1}\phi^{-1}BR^{-1}B^{T}-\phi^{T}-Q\phi^{-1}BR^{-1}B^{T})S^{T}$$
(2.23)

In the (1.2) and (2.1) subblocks of (2.23), the bracketed term of the (1.2) submatrix is zero since T_2 is the asymptotic solution to the Riccati equation whose system matrix can be represented by

$$H_{DR} = \begin{bmatrix} \phi^{-1} & \phi^{-1}BR^{-1}B^{T} \\ \\ \\ Q\phi^{-1} & \phi^{-1}+Qz^{-1}BR^{-1}B^{T} \end{bmatrix}$$
(2.24)

The (2.1) submatrix is also zero, and the system matrix is

$$H_{DR} = \begin{bmatrix} \phi^{T} + Q \phi^{-1} B R^{-1} B^{T} & Q \phi^{-1} \\ \phi^{-1} B R^{-1} B^{T} & \phi^{-1} \end{bmatrix}$$
(2.24a)

The same procedures as above are applied to H_{DR}^{-1} to determine the relation between the diagonal terms. The inverse matrix of H_{DR} in partitioned form is given as

$$H_{DR}^{-1} = \begin{bmatrix} \phi + BR^{-1}B^{T}\phi^{-T}Q & -BR^{-1}B^{T}\phi^{-T} \\ -\phi^{-T}Q & \phi^{-T} \end{bmatrix}$$
(2.25)

Applying the similarity transformation to $H_{\rm DR}^{-1}$ by \overline{V} will result in

$$\overline{\mathbf{v}}^{-1} \mathbf{H}_{DR}^{-1} \overline{\mathbf{v}} = \begin{bmatrix} \mathbf{s} & -\mathbf{s}_{2} \\ \mathbf{T}_{1} & -\mathbf{I} \end{bmatrix} \begin{bmatrix} \phi + \mathbf{BR}^{-1} \mathbf{B}^{T} \phi^{-T} \mathbf{Q} & -\mathbf{BR}^{-1} \mathbf{B}^{T} \phi^{-T} \\ -\phi^{-T} \mathbf{Q} & \phi^{-T} \end{bmatrix} \begin{bmatrix} \mathbf{I} & -\mathbf{T}_{2} \mathbf{s}^{T} \\ \mathbf{T}_{1} & -\mathbf{s}^{T} \end{bmatrix}$$

$$= \begin{bmatrix} S(\phi + BR^{-1}B^{T}\phi^{-T}Q + T_{2}\phi^{-T}Q - BR^{-1}B^{T}\phi^{-T}T_{1} - T_{2}\phi^{-T}T_{1}) \\ T_{1}\phi + T_{2}SR^{-1}B^{T}\phi^{-T}Q + \phi^{-T}Q - T_{1}BR^{-1}B^{T}\phi^{-T}T_{1} - \phi^{-T}T_{1} \end{bmatrix}$$

$$- S(\phi T_{2}^{+}BR^{-1}B^{T}\phi^{-T}QT_{2}^{+}T_{2}\phi^{-T}QT_{2}^{-}BR^{-1}B^{T}\phi^{-T}-T_{2}\phi^{-T})S^{T} - (T_{1}\phi T_{2}^{+}T_{1}BR^{-1}B^{T}\phi^{-T}QT_{2}^{+}\phi^{-T}QT_{2}^{-}T_{1}BR^{-1}B^{T}\phi^{-T}-\phi^{-T})S^{T} - (T_{2}\phi^{-}T_{2}^{+}BR^{-1}B^{T}\phi^{-}T_{2}^{-}D^{T}QT_{2}^{-}D^{T}$$

The submatrices (1.2) and (2.1) of (2.26) also vanish for the same reason as discussed previously.

In taking the inverse of both sides of (2.22a), the following is obtained:

$$H_{DR}^{-1} = \overline{V} \ \overline{H}_{DR}^{-1} \overline{V}^{-1} = \overline{V} \begin{bmatrix} H_{D1}^{-1} & 0 \\ 0 & H_{D2}^{-1} \end{bmatrix} \overline{V}^{-1}$$
(2.27)

Equating (2.26) and (2.27) and taking the transpose of the (1.1) and (2.2) subblocks yields

$$H_{D1}^{-T} = (\phi^{T} + Q^{-1}BR^{-1}B^{T} + Q\phi^{-1}T_{2}^{2T} - T_{1}^{T}\phi^{-1}BR^{-1}B^{T} - T_{1}^{T}\phi^{-1}T_{2}^{T})S^{T}$$
(2.28)

and

$$H_{D2}^{-T} = S(-T_{2}^{T}\phi^{T}T_{1}^{T}-T_{2}^{T}Q\phi^{-1}BR^{-1}B^{T}T_{1}^{T}-T_{2}^{T}Q\phi^{-1}+\phi^{-1}BR^{-1}B^{T}T_{1}^{T}+\phi^{-1})$$
(2.28a)

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Since the asymptotic solutions to Riccati equations T_1 and T_2 are symmetric matrices, it can be determined from (2.23), (2.28), and (2.28a) that

$$H_{D1} = H_{D2}^{-T}$$
 (2.29)

and

$$H_{D2} = H_{D1}^{-T}$$
 (2.29a)

It has been proven that the backward system matrix for a discrete linear regulator can be reduced to subblocks which hold the relations in (2.29) and (2.29a). The same procedure, when applied to the matrices in (2.11) and (2.11b), will uncouple the systems.

The algorithm for uncoupling the canonical equations for the discrete system is summarized in the following four steps:

- a) Obtain the state and costate difference equations to construct H_{DR} and H_{DF} .
- b) Use the bilinear transformation in (2.17) to transform the discrete system matrices into a complex plane.
- c) Obtain the transformation matrix in (2.19) by the use of matrix sign algorithm and then construct \overline{V} in (2.19a).
- Apply a similarity transformation directly to the discrete system matrices.

2.5 Generation of a Filter Matrix

A technique is developed here to generate the matrix filters by means of the sign of a matrix discussed previously. The conventional filter theory requires approximate values of the eigenvalues, and, in most cases, the eigenvalues are restricted to lie along one of the coordinate axes. [26]. In addition, the filters are not ideal, and even a weak coupling may seriously disrupt numerical calculations, accumulating errors if the filter matrices are not of sufficiently high order. In the new algorithm, the eigenvalues of a matrix are isolated into subsets in which each eigenvalue has similar characteristics, such as the same sign or the same order of magnitude. The filters constructed from the sign function are of infinite order, and there is no interaction between the eigenvalues even though closely spaced eigenvalues are separated into adjacent filters.

If it is assumed that A is an n × n system matrix of differential equations to be integrated and has the Jordan form $\Lambda = \text{diag} (\lambda_1, \lambda_2, \dots, \lambda_n)$ with a corresponding eigenvector matrix M, the sign matrix of A is then given by

sign
$$A = MKM^{-1}$$

where

$$K = diag [sign(R_e^{\lambda_1}), sign(R_e^{\lambda_2}), \dots].$$

2.5.1 Filter Matrix for Eigenvalues with the Same Sign

In the case where $\lambda_1 = \text{diag} (\lambda_1, \lambda_2, \dots, \lambda_s)$, a block for eigenvalues with positive real parts, and $\Lambda_2 = \text{diag} (\lambda_{s+1}, \dots, \lambda_n)$

for negative real parts, the sign of A is then given as

sign A = M
$$\begin{bmatrix} I_{s \times s} & 0 \\ 0 & -I_{n-s \times n-s} \end{bmatrix} M^{-1}$$
 (2.30)

The eigenvalues with positive real parts can now be isolated. The first step in the procedure is to add the identity matrix to sign A which gives

$$S_{p} = \text{sign } A+I = 2M \begin{bmatrix} I_{S \times S} & 0\\ 0 & 0 \end{bmatrix} M^{-1}$$
 (2.31)

The next step is to multiply A by the matrix S_p to form A^+ , the desired matrix,

$$A^{+} = \frac{1}{2} S_{p}A = \frac{1}{2} AS_{p} = M \begin{bmatrix} A_{1} & 0 \\ 0 & 0 \end{bmatrix} M^{-1}$$
(2.32)

Since A^{-} must be the complement of A^{+} , the eigenvalues with negative real parts are then isolated by subtracting A^{+} from A.

$$A^{-} = A - A^{+} = S_{N}A = AS_{N} = M \begin{bmatrix} 0 & 0 \\ 0 & \Lambda_{2} \end{bmatrix} M^{-1}$$
(2.32)

where

$$S_{N} = I - S_{p} = \frac{1}{2}(I - \text{sign A})$$
 (2.32a)

Thus, two fundamental filter matrices, S_p and S_N , have been generated which pass only positive and negative eigenvalues of A, respectively.

2.5.2 Filter Matrix for the Same Order of Magnitude

All eigenvalues of A may have negative real parts with $|R_e\lambda_1| < |R_e\lambda_2| < \ldots < |R_e\lambda_n|$ and be as shown in Figure 2.1. All complex eigenvalues are assumed to occur in conjugate pairs. It may also be assumed the matrix A can be separated into subblocks so that the corresponding subsets of eigenvalues, Λ_1 and Λ_2 , where $\Lambda_1 = \text{diag} (\lambda_1, \ldots, \lambda_s)$ and $\Lambda_2 = \text{diag} (\lambda_{s+1}, \ldots, \lambda_n)$ contain eigenvalues of the same order of magnitude.

Since the trace of A is equal to the sum of the eigenvalues, the mean eigenvalues of any matrix A is given by

$$L = \frac{1}{n} \operatorname{trace} A = \frac{1}{n} \sum_{K=1}^{n} \lambda_{K}$$
(2.33)

If L is assumed to be in the range of $\lambda_s > L > \lambda_{s+1}$, a simple shift of the origin of the eigenvalues space can be made so that the subset Λ_1 lies in the positive domain and Λ_2 in the negative domain.



Figure 2.1

If L is as shown in Figure 2.1, a shift of the origin by -LI will produce a new matrix $A_L = A$ -LI, and A_L can be written as

The sign of A_{r.} will be of the form

sign
$$A_{L} = M \begin{bmatrix} I_{S \times S} & 0 \\ 0 & -I_{n-S \times n-S} \end{bmatrix} M^{-1}$$
 (2.35)

Either of the subblocks in (2.35) can be isolated by adding or subtracting the identity matrix I of the order $n \times n$.

Since $|R_e \lambda_1| < |R_e \lambda_2| < \ldots < |R_e \lambda_n|$, the subset Λ_1 represents the eigenvalues with the smaller $|R_e \lambda_1|$. This set of eigenvalues should be included in the low pass filter. The low pass filter, S_{Lp} , is then

$$S_{Lp} = S_1 = \frac{1}{2} [1 + sign(A - LI)] = MU_1 M^{-1}$$
 (2.36)

where

$$U_{1} = \text{diag} (U_{11}, \dots, U_{n1}), \text{ and}$$
$$U_{11} = \begin{cases} 1 & i = 1, \dots, S \\ 0 & i = s+1, \dots, n \end{cases}$$

The trace of S_1 will be an integer which is equal to the number of eigenvalues in the subset Λ_1 . The product S_1A or AS_1 isolates the subset Λ_1 so that

$$A_{1} = S_{1}A = AS_{1} = M \begin{bmatrix} \Lambda_{1} & 0 \\ 0 & 0 \end{bmatrix} M^{-1}$$
 (2.37)

where the trace of A , equals the trace of A ,

Since the high pass filter S_{Hp} is the complement of S_{Lp} ,

$$S_{Hp} = S_2 = I - S_{Lp} = \frac{1}{2} [I - sign(A - LI)]$$

= $MU_2 M^{-1}$ (2.38)

where $U_2 = \text{diag} (U_{21}, \dots, U_{2n})$, and

$$U_{i2} = \begin{cases} 0 & i = 1, \dots, s \\ 1 & i = s+1, \dots, n \end{cases}$$

then Λ_2 is isolated as

$$A_2 = S_2 A = AS_2 = M \begin{bmatrix} 0 & 0 \\ 0 & \Lambda_2 \end{bmatrix} M^{-1}$$
 (2.39)

2.5.3 Band-pass Filter Matrix

A band-pass filter matrix is now derived for the set of eigenvalues with intermediate magnitude. The case where $\Lambda_1 = \text{diag } (\lambda_1, \dots, \lambda_r), \Lambda_2 = \text{diag } (\lambda_{r+1}, \dots, \lambda_s)$ and $\Lambda_3 = \text{diag } (\lambda_{s+1}, \dots, \lambda_n)$ is shown in Figure 2.2.

The generation of the high-pass matrix, $\rm S_{hp}$ is analogous to the previous case. $\rm S_{hp}$ is then

$$S_{hp} = S_3 = \frac{1}{2} [I - sign (A - LI)]$$

= $MU_3 M^{-1}$ (2.40)

where $U_3 = \text{diag} (U_{13}, \dots, U_{n3})$ and

$$U_{i3} = \begin{cases} 0 & i = 1, \dots, r \\ 0 & i = r \div 1, \dots, s \\ 1 & i = s \div 1, \dots, n \end{cases}$$

The matrix with the isolated subset $\boldsymbol{\Lambda}_3$ becomes

$$A_{3} = S_{3}A = AS_{3} = M \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & \Lambda_{3} \end{bmatrix} M^{-1}$$
 (2.41)

To form the low-pass filter matrix, trace A_3 should be subtracted from trace A and the remainder should be divided by the number of remaining eigenvalues for a second shift of the origin

$$L_1 = \frac{\text{trace } A - \text{trace } A_3}{n - \text{trace } S_3}$$
(2.42)

which is assumed to be equal to L_1 on Figure 2.2.



Figure 2.2

The new shifted matrix is then

$$A_{L1} = \dot{A} - L_{1} I = M \Lambda M^{-1} - L_{1} I$$

$$= M \begin{bmatrix} \lambda_{1} - L_{1} & & \\ & \lambda_{2} - L_{1} & \\ & & \ddots & \\ & & & \ddots & \\ & & & & \lambda_{n-L} \end{bmatrix} M^{-1}$$
(2.43)

and the sign of ${\rm A}^{}_{\rm L1}$ is found as shown in

sign A_{L1} = M
$$\begin{bmatrix} I_{r \times r} & 0 \\ 0 & -I_{n-r \times n-r} \end{bmatrix} M^{-1}$$
(2.44)

Since the subset Λ_1 represents the low-pass filter,

$$S_{Lp} = S_1 = \frac{1}{2} (\text{sign } A_{L1} + I)$$

= $MU_1 M^{-1}$ (2.45)

where

$$U_1 = \text{diag}(U_{11}, \dots, U_{n1})$$
, and

$$U_{i1} = \begin{cases} 1 & i=1,...,r \\ 0 & i=r+1,...,s \\ 0 & i=s+1,...,n \end{cases}$$

Similar to S_{Hp} , the trace of S_1 is equal to the number of eigenvalues in subset Λ_1 . The isolation of Λ_1 is given below:
$$A_{1} = S_{1}A = AS_{1} = M \qquad \begin{array}{ccc} & \Lambda_{1} & 0 & 0 \\ 0 & 0 & 0 & M^{-1} \\ 0 & 0 & 0 \end{array} \qquad (2.46)$$

The band-pass filter $\rm S_{Bp}$ must be the complement of $\rm S_{Lp}$ and $\rm S_{Hp};$ that is,

$$S_{Bp} = I - S_{Lp} - S_{Hp}$$

Then S_{Bp} is expressed as

$$S_{Bp} = MU_2 M^{-1}$$
 (2.47)

where

$$\mathbf{U}_2 = \text{diag}(\mathbf{U}_{12}, \dots, \mathbf{U}_{n2}), \text{ and}$$

$$U_{i2} = \begin{cases} 0 & i = 1, \dots, r \\ 1 & i = r+1, \dots, s \\ 0 & i = s+1, \dots, n \end{cases}$$

The eigenvalues in the subset Λ_2 can now be isolated directly by forming Λ_2 as

$$A_{2} = A - A_{1} - A_{3} = M \begin{bmatrix} 0 & 0 & 0 \\ 0 & A_{2} & 0 \\ 0 & 0 & 0 \end{bmatrix} M^{-1}$$
(2.48)

Any number of band-passfilters can be generated by the origin shifting procedure outlined for $S_{\rm Hp}$ and $S_{\rm Lp}$.

The algorithm described above does not consider the imaginary part ω_i of any complex eigenvalue. The imaginary parts can be examined since knowledge of ω_i for such eigenvalues may be important for the integration of step sizes. This examination can be accomplished by rotating the spectrum of any A_i .

To rotate the spectrum, A_i can be multiplied by j in which case the sign algorithm becomes

$$(\text{sign jA})^{i+1} = \frac{1}{2}(\text{sign jA})^{i} + \frac{1}{2}((\text{sign jA})^{i})^{-1}$$
 (2.49)

Since j is a scalar, (2.49) can be written as

$$(\text{sign A})^{i+1} = \frac{1}{2}(\text{sign A})^{i} - \frac{1}{2}((\text{sign A})^{i})^{-1}$$
 (2.49a)

which is the desired form for the rotated spectrum. The imaginary parts of the eigenvalues have now been mapped into the real domain and the real parts into the imaginary. The sign matrix of the rotated matrix will be the identity matrix if all imaginary parts of the eigenvalues are zero or are of the same sign.

The magnitude of ω_i can be determined by a shift of the origin of the rotated matrix.

2.6 Examples

Two example problems are designed to illustrate the numerical procedure and the properties of uncoupled systems. Examples for a matrix filter generation will be given in Chapter V.

2.6.1 Continuous System Matrix

The backward system matrix for a linear regulator was obtained using the following coefficient matrices:

$$A = \begin{bmatrix} 0.0 & 1.0 \\ 2.0 & -1.0 \end{bmatrix} B = \begin{bmatrix} 0.0 \\ 1.0 \end{bmatrix} Q = \begin{bmatrix} 2.0 & 0.0 \\ 0.0 & 1.0 \end{bmatrix} \text{ and } R = [1.0]$$

which give

$$H_{CR} = \begin{bmatrix} 0.0 & -2.0 & | & -2.0 & 0.0 \\ -1.0 & 1.0 & 0.0 & -1.0 \\ 0.0 & 0.0 & 0.0 & 1.0 \\ 0.0 & -2.0 & | & 2.0 & -1.0 \end{bmatrix}$$

A transformation matrix is constructed from the sign function of $$^{\rm H}_{\rm CR}$ as}$

$$\overline{\mathbf{v}} = \begin{bmatrix} 1.0 & 0.2220 - 15 & -1.556 & -0.1988 \\ -0.2220 - 15 & 1.0 & -0.1988 & -0.4798 \\ -0.6786 & -0.7189 & -0.8012 & 0.4798 \\ -0.7189 & -1.2005 & 1.3572 & -1.2811 \end{bmatrix}$$

The uncoupled system matrix is then formed by the similarity transforms

$$\overline{\mathbf{v}}^{-1}\mathbf{H}_{CR}\overline{\mathbf{v}} = \begin{bmatrix} 1.3572 & -0.5622 & 0.2617-15 & -0.3451-17 \\ -0.2811 & 2.2005 & 0.1388-15 & -0.1388-15 \\ -0.1388-15 & 0.1388-16 & -1.35722 & 0.2811 \\ -0.4302-15 & -0.441-15 & 0.5622 & -2.2005 \end{bmatrix}$$

$$= \begin{bmatrix} {}^{H}Cl & 0 \\ 0 & {}^{H}C2 \end{bmatrix}$$

The desired relationship has been established between submatrices $H_{C1} = -H_{C2}^{T}$.

2.6.2 Discrete System Matrix

The block diagonalization procedure for a discrete system matrix is illustrated by a numerical example. The coefficient matrices considered are

$$\phi = \begin{bmatrix} -1.0 & 0.0 & 0.0 \\ 0.0 & 0.0 & 2.0 \\ 0.0 & -2.0 & 0.0 \end{bmatrix} G = \begin{bmatrix} 2.0 \\ 2.0 \\ -1.0 \end{bmatrix} R = [1.0] \text{ and}$$
$$Q = \begin{bmatrix} 1.0 & 1.0 & 0.0 \\ -1.0 & 1.0 & 0.0 \\ 0.0 & 0.0 & 0.0 \end{bmatrix}$$

which give a forward system matrix in the discrete domain

$$H_{DR} = \begin{bmatrix} -6.0 & 5.0 & 0.0 & 4.0 & -1.0 & -2.0 \\ -5.0 & 5.0 & 2.0 & 4.0 & -1.0 & -2.0 \\ 2.5 & -4.5 & 0.0 & -2.0 & 0.5 & 1.0 \\ \hline 1.0 & -1.0 & 0.0 & -1.0 & 0.0 & 0.5 \\ 0.0 & 0.0 & 0.0 & 0.0 & 0.0 & 0.5 \\ -0.5 & 0.5 & 0.0 & 0.0 & -0.5 & 0.0 \end{bmatrix}$$

Now H_{DR} is transformed to the complex plane by the following:

$$(H_{DR}+I)^{-1}(H_{DR}-I) = \begin{bmatrix} 1.8 & -0.4 & 0.8 & -2.0 \\ 0.8 & 0.6 & 0.8 & 0.1332-15 \\ 0.6 & -0.8 & 0.6 & 1 & -0.3331-16 \\ -0.5 & 0.1249-15 & 0.1631-16 & -1.8 \\ 0.4163-16 & -0.4163-16 & 0.1388-17 & -0.4 \\ -0.5551-16 & 0.4163-16 & -0.2776-17 & -0.8 \end{bmatrix}$$

| 0.1388-15 | ך 0.1388-15 |
|-----------|-------------|
| 0.9853-16 | 0.8604-16 |
| 0.8119-16 | 0.7910-16 |
| -0.8 | -0.6 |
| -0.6 | 0.8 |
| -0.8 | -0.6 |

A transformation matrix is constructed as before

| | Γ1.0 | 0.1337-16 | 0.2255-16 | -1.0518 | 0.1942 |
|------------|------------|------------|------------|------------|------------|
| | 0.1789-17 | 1.0 | -0.1301-16 | 0.1942 | -0.1295 |
| <u>v</u> = | -0.1735-17 | -0.2602-17 | 1.0 | 0.4147 | -0.9710-01 |
| - | -0.1476 | 0.2289-02 | 0.5948-01 | -1.8196 | -0.3474-01 |
| | 0.2289-02 | -0.1356-01 | -0.1132-01 | -0.9733-02 | -1.9967 |
| | 0.5948-01 | -0.1132-01 | -0.5832-01 | -0.8895-01 | 0.1868-01 |
| | | | | | |

 $\begin{array}{c} 0.4147 \\ -0.9710-01 \\ -0.5442 \\ -0.9382-01 \\ 0.8424-02 \\ -1.9425 \end{array}$

A similarity transformation can be applied directly on ${\rm H}^{}_{\rm DR}$ by \overline{V}

| | [H _{D1} | 0] |
|------------------|------------------|-------------------|
| $V = H_{DR} V =$ | L o | ₽ _{D2}] |

| | F 6.7118 | -5.0453 | -0.3659 | |
|----|--------------|------------|--------------|---|
| | 5.7118 | -5.0453 | -2.3659 | |
| II | -2.8559 | 4.5227 | 0.1829 | |
| | 0.1091-15 | -0.1440-15 | 0.1663-16 | |
| | -0.1530-15 | 0.1278-15 | 0.1723-16 | |
| | L -0.1847-15 | 0.1995-15 | 0.1524-17 | |
| | | | | |
| | 0.4230-15 | -0.6705-15 | -0.5794-15 - | ך |
| | 0.5783-15 | -0.7389-15 | -0.7072-15 | |
| | 0.1656-15 | 0.4004-15 | 0.7638-16 | |
| | 0.2997 | 0.1751 | 0.3502 |] |
| | -0.2243-01 | 0.5608-02 | -0.4888 | ļ |
| | 0.3093 | 0.4227 | -0.1547 - | J |

where the inverse is

$$\overline{\nabla}^{-1} H_{DR}^{-1} \overline{\nabla} = \begin{bmatrix} H_{D1}^{-1} & 0 \\ 0 & H_{D2}^{-1} \end{bmatrix}$$

| [| 0.2997 | -0.2243-01 | 0.3093 |
|---|------------|------------|-------------|
| | 0.1751 | 0.5608-02 | 0.4227 |
| _ | 0.3052 | -0.4888 | -0.1547 |
| | -0.4944-16 | 0.1179-15 | 0.2547-15 |
| | 0.7383-16 | -0.1061-15 | -0.2536-15 |
| L | 0.3260-16 | -0.1537-16 | -0.6397-17 |
| | | | |
| | -0.1462-14 | -0.1565-14 | ך 0.7695-15 |
| | -0.7747-15 | -0.7736-15 | 0.2183-15 |
| | 0.1448-14 | 0.1450-14 | -0.7729-15 |
| | 6.7118 | 5.7118 | -2.8559 |
| | -5.0453 | -5.0453 | 4.5227 |
| | -0.3659 | -2.3659 | 0.1829 |

which results in the expected relation $H_{D1} = H_{D2}^{-T}$.

2.6.3 Filter Matrix

The A matrix to illustrate the filter matrix generation was constructed from $A = M\Lambda M^{-1}$ with

 $\Lambda = \text{diag} [-1200 -500 -1.5 -0.5]$

and

$$M = \begin{bmatrix} 0 & 1 & 2 & 2 \\ 1 & 1 & 2 & 3 \\ 2 & 2 & 2 & 3 \\ 2 & 3 & 3 & 3 \end{bmatrix}$$

Three filter matrices were computed, a low pass which contained $\lambda = -1.5$, and -0.5, a band pass with $\lambda = -500$ and a high pass with $\lambda = -1200$. The filter matrices are given below

$$S_{LP} = S_{1} = \begin{bmatrix} -2 & 4 & -4 & 2 \\ -0.1E-15 & 2 & -1 & 0.1E-15 \\ -0.2E-15 & 2 & -1 & 0.2E-15 \\ -2 & 6 & -6 & 3 \end{bmatrix}$$

$$S_{BP} = S_2 = \begin{bmatrix} 3 & -4 & 4 & -2 \\ 3 & -4 & 4 & -2 \\ 6 & -8 & 8 & -4 \\ 9 & -12 & 12 & -6 \end{bmatrix}$$

.

and

$$S_{HP} = S_3 = \begin{bmatrix} -0.18E - 15 & -0.18E - 15 & -0.18E - 15 \\ -3 & 3 & -3 \\ -6 & 6 & -6 \\ -6 & 6 & -6 \end{bmatrix}$$

.

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CHAPTER III

SOLUTION OF THE UNCOUPLED CONTINUOUS SYSTEM

3.1 Linear Systems with Quadratic Criteria

The theory of the linear optimal regulator problem is well known and documented [9,39]. The process is controlled by the state equation

$$X(t) = A x(t) + BU(t)$$
 (3.1)

with the initial condition

$$X(t_0) = X_0$$
 (3.1a)

The desired system is brought from an initial state X_0 to a terminal state $X(t_f)$ using acceptable levels of control U(t) and the state X(t) on the trajectory. One way to accomplish this is to minimize a cost functional. This functional is made up of a positive definite quadratic form in the terminal state, in addition to an integral of positive definite quadratic forms in the state and the control as shown below:

$$J(U) = \frac{1}{2} X^{T} (t_{f}) H x (t_{f}) + \frac{1}{2} \int_{t_{0}}^{t_{f}} [X^{T}(t)QX(t) + U^{T}(t)RU(t)]dt$$
(3.2)

where the final time t_f is fixed, H and Q are real symmetric positive semi-definite matrices, and R is a real symmetric positive definite matrix.

It is assumed that the state and controls are not bounded and $X(t_f)$ is free. The problem is solved via the Pontryagin maximum principle c r the Hamilton-Jacobi equation. Here, the former method is used.

The Hamiltonian is formed by introducing the costate vector $\lambda(t)$ as

$$H[X(t), U(t), \lambda(t), t] = \frac{1}{2} X^{T}(t) QX(t) + \frac{1}{2} U^{T}(t) RU(t) + \lambda^{T}(t) AX(t) + \lambda^{T}(t) BU(t)$$
(3.3)

The necessary conditions for the optimality are

$$X(t) = AX(t) + BU(t)$$
 (3.4)

$$\dot{\lambda}(t) = -QX(t) - A^{T}\lambda(t)$$
(3.4a)

$$U(t) = -R^{-1}B^{T}\lambda(t)$$
 (3.4b)

with the terminal condition

$$\lambda(t_f) = HX(t_f)$$
(3.4c)

Substituting (3.4b) for (3.4) and repeating (3.4a), the following linear two-point boundary-value problem may be developed:

$$\begin{bmatrix} \dot{X}(t) \\ \dot{\lambda}(t) \end{bmatrix} = H_{CR} \begin{bmatrix} X(t) \\ \lambda(t) \end{bmatrix}$$
(3.5)

where H_{CR} is the system matrix associated with the continuous system with a quadratic performance index with coefficient matrices as follows:

$$H_{CR} = \begin{bmatrix} A & -BR^{-1}B^{T} \\ -Q & -A^{T} \end{bmatrix}$$
(3.5a)

Since the problem is linear, and the differential equations are homogeneous, it is clear that both X(t) and λ (t) are proportional to X₀. All existing solutions to this boundary value problem are designed to obtain the linear relation between the state and costate vectors, denoted by the feedback optimal gain matrix.

3.1.1 Solution by a Transition Matrix

The solutions to (3.5) may have the form

$$\begin{bmatrix} \mathbf{X}(\mathbf{t}_{\mathbf{f}}) \\ \lambda(\mathbf{t}_{\mathbf{f}}) \end{bmatrix} = \begin{bmatrix} \phi_{11}(\mathbf{t}_{\mathbf{f}}^{\pm}) & \phi_{12}(\mathbf{t}_{\mathbf{f}}^{\pm}) \\ \phi_{21}(\mathbf{t}_{\mathbf{f}}^{\pm}) & \phi_{22}(\mathbf{t}_{\mathbf{f}}^{\pm}) \end{bmatrix} \begin{bmatrix} \mathbf{X}(\mathbf{t}) \\ \lambda(\mathbf{t}) \end{bmatrix}$$
(3.6)

where ϕ_{ij} are n × n partitions of the transition matrix of (3.5). Substituting (3.6) for the terminal condition (3.4c),

$$H\phi_{11}(t_{f'}t)X(t) + H\phi_{12}(t_{f'}t)\lambda(t) = \phi_{21}(t_{f'}t)X(t) + \phi_{22}(t_{f'}t)\lambda(t)$$

The solution for $\lambda(t)$ may be written as

$$\lambda(t) = p(t)X(t)$$
(3.7a)

where

$$p(t) = [\phi_{22}(t_{f'}t) = H\phi_{12}(t_{f'}t)] - 1 [H\phi_{12}(t_{f'}t) - \phi_{21}(t_{f'}t)]$$
(3.7b)

3.1.2 Solution by the Riccati Equation

The idea of an alternative approach is contained in (3.7a) and (3.7b). The value p(t) is determined directly by integrating a matrix Riccati equation derived in the following procedures:

Substituting (3.7a) for (3.4a) yields

$$\dot{p}(t)X(t) + p(t)\dot{X}(t) = -QX(t) - A^{T}\lambda(t)$$
 (3.8)

Next, substituting X(t) from (3.1) into (3.8) and using (3.7a) again,

$$[p(t)+p(t)A(t)+A^{T}(t)p(t)-p(t)BR^{-1}B^{T}p(t)+Q]X(t) = 0$$
(3.8a)

Since $X(t) \neq 0$, (3.8a) requires that

$$p(t) = -p(t)A - A^{T} p(t) + p(t)BR^{-1}B^{T}p(t) - Q$$
 (3.8b)

From the terminal condition in (3.4c), it is evident that

$$p(t_f) = H$$
 (3.8c)

Since p(t) is an n × n symmetric matrix, it is necessary to solve the n(n + 1)/2 first-order differential equations. Many numerical techniques have been developed to solve the matrix Riccati equation efficiently. In general, the integration is started at t = t_f and proceeds backward in time to t = t_0 , and p(t) is stored for the feedback law and optimum state. It is then possible to determine $\lambda(t_0)$ from (3.7a) as follows:

$$\lambda(t_0) = p(t_0)X(t_0)$$
(3.9)

which may be regarded as the equivalent of the terminal boundary condition in (3.4c) at an earlier time. An alternate method has been derived to obtain the solution to (3.6) by forward integration, since $\lambda(t_0)$ and $X(t_0)$ are both known (15,31,34).

3.1.3 The Hamilton-Jacobi-Bellman Equation

The Hamilton-Jacobi-Bellman equation can be used as a means of solving the general form of the continuous linear regulator problem [23]. The Hamiltonian for the use of Hamilton-Jacobi-Bellman equation is formed in this case by the following:

$$H[X(t), U(t), J_{X}, t] = \frac{1}{2}X^{T}(t)QX(t) + \frac{1}{2}U^{T}(t)RU(t) + J_{X}^{T}(X(t), t)$$

$$\cdot [AX(t) + BU(t) \qquad (3.10)$$

A necessary condition for U(t) to minimize H is that $\frac{\partial H}{\partial U} = 0$; thus,

$$U(t) = -R^{-1}B^{T}J_{X}(X(t),t)$$
 (3.11)

which, when substituted in (3.10), yields

$$H(X,U,J_{X},t) = \frac{1}{2}X^{T}QX - \frac{1}{2}J_{X}^{T}BR^{-1}B^{T}J_{X} + J_{X}^{T}AX \qquad (3.12)$$

Now the Hamilton-Jacobi-Bellman equation is

$$0 = J_{t} + \frac{1}{2}X^{T}QX - \frac{1}{2}J_{X}^{T}BR^{-1}B^{T}J_{X} + J_{X}^{T}AX$$
(3.13)

with the boundary condition

$$J(X(t_{f}), t_{f}) = \frac{1}{2}X^{T}(t_{f}) HX(t_{f})$$
(3.13a)

It is assumed that the minimum cost for the linear regulator problem is a quadratic function of the state and has the form

$$J[X(t),t] = \frac{1}{2}X^{T}(t)p(t)X(t)$$
 (3.14)

where p(t) is a real symmetric positive-definite matrix to be

determined.

Substituting (3.16) in (3.13) and using the property of symmetric matrix,

$$\dot{p}(t) = -Q - p(t) BR^{-1} B^{T} p(t) - p(t) A - A^{T} p(t)$$
(3.15)

and the boundary condition obtained from (3.13a) and (3.14) is

$$p(t_{f}) = H$$
 (3.15a)

In the derivation of the Riccati equation developed in (3.8b) and (3.8c), the equation (3.13) gives another interpretation of the meaning of p(t); that is, $\frac{1}{2}x^{T}(t)p(t)X(t)$ is the minimum value of the cost function starting at time t with state vector X(t).

3.2 A Reduced Linear Regulator

The uncoupling algorithm based on the matrix block diagonalization can be a powerful tool in solving a two-point boundary value problem. By reducing the system order to be integrated, the determination of the missing initial condition will be faster and more accurate. An efficient method for the solution of a linear regulator is studied in this section. This technique can be extended easily to other optimal controls and estimation problems with quadratic criteria since their system matrices have a structure analogous to that of the linear regulator.

The vectors y(t) and u(t) are defined by the relation

$$\begin{bmatrix} X(t) \\ \lambda(t) \end{bmatrix} = \begin{bmatrix} V_{11} & V_{12} \\ V_{21} & V_{22} \end{bmatrix} \begin{bmatrix} Y(t) \\ \omega(t) \end{bmatrix}$$
(3.16)

where the elements of V_{ij} are given by (2.9a).

Differentiating both sides of (3.16) and substituting (3.5) for it,

$$\begin{bmatrix} \dot{\mathbf{x}} \\ \dot{\mathbf{\lambda}} \end{bmatrix} = \mathbf{H}_{\mathrm{CR}} \begin{bmatrix} \mathbf{x} \\ \mathbf{\lambda} \end{bmatrix} = \mathbf{H}_{\mathrm{CR}} \begin{bmatrix} \mathbf{v}_{11} & \mathbf{v}_{12} \\ \mathbf{v}_{21} & \mathbf{v}_{22} \end{bmatrix} \begin{bmatrix} \mathbf{y} \\ \mathbf{\omega} \end{bmatrix} = \begin{bmatrix} \mathbf{v}_{11} & \mathbf{v}_{12} \\ \mathbf{v}_{21} & \mathbf{v}_{22} \end{bmatrix} \begin{bmatrix} \dot{\mathbf{y}} \\ \dot{\mathbf{\omega}} \end{bmatrix}$$
(3.17)

from which

$$\begin{bmatrix} \dot{\mathbf{y}}(t) \\ \vdots \\ \dot{\boldsymbol{\omega}}(t) \end{bmatrix} = \begin{bmatrix} \mathbf{v}_{11} & \mathbf{v}_{12} \\ \mathbf{v}_{21} & \mathbf{v}_{22} \end{bmatrix}^{-1} \qquad \mathbf{H}_{CR} \begin{bmatrix} \mathbf{v}_{11} & \mathbf{v}_{12} \\ \mathbf{v}_{21} & \mathbf{v}_{22} \end{bmatrix} \begin{bmatrix} \mathbf{y}(t) \\ \vdots \\ \boldsymbol{\omega}(t) \end{bmatrix}$$
(3.18)

Using the result given by (2.10), the uncoupled system equation for the linear regulator becomes

$$\begin{bmatrix} \mathbf{y}(t) \\ \vdots \\ \omega(t) \end{bmatrix} = \begin{bmatrix} \mathbf{H}_{C1} & \mathbf{0} \\ \mathbf{0} & -\mathbf{H}_{C1}^{T} \end{bmatrix} \begin{bmatrix} \mathbf{y}(t) \\ \vdots \\ \omega(t) \end{bmatrix}$$
(3.18a)

If $\psi(t \neq_0)$ is the state transition matrix for the unij coupled system (5.18a), it follows that

$$\begin{bmatrix} \dot{\psi}_{11}(t,t_{0}) & 0 \\ 0 & \dot{\psi}_{22}(t,t_{0}) \end{bmatrix} = \begin{bmatrix} H_{C1} & 0 \\ 0 & -H_{C1}^{T} \end{bmatrix} \begin{bmatrix} \psi_{11}(t,t_{0}) & 0 \\ 0 & \psi_{22}(t,t_{0}) \end{bmatrix}$$
(3.19)

where the partitions of ψ, ψ_{11} , and ψ_{22} are the state transition matrices for the system equations y(t) and $\omega(t)$, respectively.

The initial conditions for (3.19) are

$$\psi_{11}(t_0, t_0) = \psi_{22}(t_0, t_0) = I$$
 (3.19a)

A direct series expansion has been adopted to integrate (3.19) and (3.19a) for an increment of time t.

$$\Delta \psi_{11} = \psi_{11}(t + \Delta t, t_0) = \exp(\overline{H}_{C1}\Delta t) = I + H_{C1}\Delta t$$
$$+ \frac{(H_{C1})^2 \Delta t^2}{2!} + \frac{(H_{C1})^3 \Delta t^3}{3!} + \dots \qquad (3.19b)$$

The following recursive equations carry on the forwarding integration

$$y_{i+1} = \Delta \psi_{11} y_i$$
 (3.19c)

$$\omega_{i+1} = \Delta \psi_{22} \omega_i \tag{3.19d}$$

and it can be seen from (3.18a) that the differential equation $\dot{\omega} = -H_{Cl}^{T}\omega$ is the adjoint to the system equation $\dot{y} = H_{Cl}^{T}y$.

The importance of this fact is that there exists a relationship between the state transition matrices of the adjoint system and the original system so that

$$\psi_{22}(t t_0) = \psi_{11}^{\mathrm{T}}(t t_0)^{-1}$$
(3.20)

This relationship will reduce the computational effort so that it is necessary to solve only one differential equation, either $\dot{y}(t)$ or $\dot{\omega}(t)$.

Another advantage of the adjoint system is that the physically realizable solution of the adjoint system represents the physically unrealizable portion of the solution of the original system.

Now the solution vectors y(t) and $\omega(t)$ are given by

$$y(t) = \psi_{11}(t, t_0) y(t_0)$$
 (3.21)

and

$$\omega(t) = (\psi_{11}^{T}(t, t_{0}))^{-1} \omega(t_{0})$$
(3.21a)

The initial conditions $y(t_0)$ and $\omega(t_0)$ must be determined to complete the formulation. Using the relationship between the coupled and uncoupled solution vectors defined by (3.16), the terminal condition in (3.4c) can be rewritten as

$$V_{21}Y(t_{f}) + V_{22}\omega(t_{f}) = H[V_{11}Y(t_{f}) + V_{12}\omega(t_{f})]$$
(3.22)

from which a new terminal condition is defined as

$$Y(t_f) = \overline{H}\omega(t_f)$$
(3.22a)

where

$$\overline{H} = -(V_{21} - HV_{11})^{-1}(V_{22} - HV_{12})$$
(3.22b)

H represents a terminal weighting matrix for the uncoupled system.

Substituting $Y(t_f)$ and $\omega(t_f)$ in (3.21) and (3.21a) for (3.22a) and solving for $y(t_0)$ results in

$$y(t_0) = S_0 \omega(t_0)$$
 (3.23)

where

$$s_{0} = [\psi_{11}(t_{f}t_{0})]^{-1} \overline{H}[\psi_{11}^{T}(t_{f}t_{0})]^{-1}$$
(3.23a)

The initial conditions for the uncoupled system are determined from the given initial condition X_0 . Using (3.16) again,

$$\omega(t_0) = (V_{11}S_0 + V_{12})^{-1} X_0$$
 (3.24)

and

$$y(t_0) = S_0 \omega(t_0) = (V_{11} + V_{12} S_0^{-1})^{-1} X_0$$
 (3.24a)

The desired solution for the original system equations can then be reconstructed from the solution of the uncoupled system

$$\begin{bmatrix} \mathbf{X}(t) \\ \lambda(t) \end{bmatrix} = \begin{bmatrix} \mathbf{V}_{11} & \mathbf{V}_{12} \\ \mathbf{V}_{21} & \mathbf{V}_{22} \end{bmatrix} \begin{bmatrix} \mathbf{U}_{11}(t, \mathbf{t}_0) & \mathbf{0} \\ \mathbf{U}_{11}(t, \mathbf{t}_0) & \mathbf{U}_{11}(t, \mathbf{t}_0) \end{bmatrix} \begin{bmatrix} \mathbf{Y}(t_0) \\ \mathbf{U}(t_0) \end{bmatrix}$$
(3.25)

The technique described offers several advantages over conventional methods. The main advantage is that there is no need for any calculation of the feedback gain matrix, thus eliminating costly storage problems. Since the uncoupled system equations are adjoint to each other, the $2n \times 2n$ original coupled system is transformed to an $n \times n$ subsystem without changing any system characteristics.

The missing initial condition λ_0 can be obtained from (3.24) and (3.24a).

$$\lambda_0 = P_0 X_0 \tag{3.26}$$

where

$$P_{0} = (V_{21}S_{0} + V_{22}) (V_{11}S_{0} + V_{12})^{-1}$$
(3.26a)

It can be seen that P₀ is the initial condition in Riccati equations for the continuous optimal feedback gain of linear regulators (3.8b) and is equivalent to the kickback equation in the matrix increment coefficient (MIC) algorithm developed earlier [31,34].

Recalling that the solution matrix P(t) of the Riccati equation is defined by $\lambda(t) = p(t)x(t)$, and using the relation in (3.16), P(t),

$$P(t) = [V_{21}Y(t) + V_{22}\omega(t)] [V_{11}Y(t) + V_{12}\omega(t)]^{-1}$$
(3.27)

Substituting (3.21), (3.21a), and (3.23) for (3.27), p(t) becomes

$$P(t) = [v_{21}\psi_{11}(t,t_0)s_0 + v_{22}\psi_{11}^T(t,t_0)]$$

$$(3.27a)$$

$$[v_{11}\psi_{11}(t,t_0)s_0 + v_{12}\psi_{11}^T(t,t_0)]^{-1}$$

At t = t_0 , the value P(t_0) is obtained. This value is equivalent to P₀ in (3.26a). Equation (3.27a) is an algebraic expression for the optimal feedback gain in the linear regulator. This procedure can be applied to the estimation problem, and an algebraic solution for the covariance matrix can be obtained.

Since the reduced subblock H_{Cl} is assumed to contain positive eigenvalues only, the inverse of its transition matrix

is numerically stable and will vanish when the terminal time becomes infinite. The situation in which the process is to be controlled for an interval of infinite duration attracts special attention in the performance evaluation of many types of linear filtering, prediction, and optimum controls. In general, the terminal weighting matrix H is assumed to be zero.

When the terminal time is infinite, the uncoupled systems have simpler solutions as follows:

Since $S_0 = 0$ as $t_{f} \rightarrow \infty$

$$t_{f}^{\lim} \omega(t_{0}) = V_{12}^{1} x_{0} \qquad (3.28)$$

and

$$\lim_{t \to \infty} y(t_0) = 0$$
(3.28a)

Therefore, from (3.21) and (3.21a),

$$y(t) = 0$$
 (3.29)

and

$$\omega(t) = \left[\psi_{11}^{\mathrm{T}}(t t_{0})\right]^{-1} v_{12}^{-1} x_{0} \qquad (3.29a)$$

The steady state solutions for the original system be-

$$X(t) = V_{12} [\psi_{11}^{T}(t t_{0})]^{-1} V_{12}^{-1} X_{0}$$
(3.30)

$$\lambda(t) = V_{22} \left[\psi_{11}^{T}(t t_{0}) \right]^{-1} V_{12}^{-1} X_{0}$$
 (3.30a)

The steady state solution for p(t) can be obtained either from (3.27a) or (3.30) and (3.30a). Both cases result in

$$\lim_{t_{f} \to \infty} p(t) = V_{22} V_{12}^{-1} = S^{T} (T_{2} S^{T})^{-1}$$
$$= T_{2}^{-1} = M_{22} M_{12}^{-1}$$
(3.31)

which is equivalent to the conventional positive definite solution of a matrix quadratic equation [28,33]. In many practical problems, the steady state solutions have been implemented without significant performance degradation to compare system performance using the time varying optimal gain.

The algorithm for solving the constant coefficient linear regulator problem can be summarized in the six steps below:

- a) Obtain the state and costate equations to construct . H_{CR}.
- b) Use the sign algorithm to construct the transformation matrices V and $\overline{V}.$
- c) Compute $\psi_{11}(t_f \neq_0)$ (or $\psi_{22}(t_f \neq_0)$ from (3.19b) and (3.19c).
- d) Obtain a new terminal weighting matrix H as given in (3.22b).
- e) Compute S_o from (3.23a).
- f) Compute new initial condition vectors as specified in (3.24) and (3.24a).
- g) Reconstruct solution vectors for a coupled systemby (3.25).

3.3 Examples

The algorithm has been used to solve numerous linear regulator problems. There is excellent agreement when results obtained by using the algorithm are compared with results obtained by using other computational procedures. Two examples will be discussed. The numerical values given were obtained by using the algorithm and by using a procedure for the EISPAK subroutine package.

The state equations for the first example are as follows:

 $\dot{X}(t) = Ax(t) + Bu(t)$

| | ٦ | -0.21053 | -0.10526 | -0.000 | 07378 | 0.0 | 0.0706 | 0.0] |
|------------------|---|--------------------|----------|--------|-------|-------|----------|-------|
| A = | | 1.0 | -0.03537 | -0.000 | 01180 | 0.0 | 0.0004 | 0.0 |
| | = | 0.0 | 0.0 | 0.0 | | 1.0 | 0.0 | 0.0 |
| | | 0.0 | 0.0 | -605. | 16 | -4.92 | 0.0 | 0.0 |
| | | 0.0 | 0.0 | 0.0 | | 0 | 0.0 | 1.0 |
| | L | 0.0 | 0.0 | 0.0 | | 0 | -3906.25 | -12.5 |
| B^{T} | - | [-7.211 | -0.05232 | 0.0 | 1.0 | 0.0 | -1.0] | |
| Q | = | [I] _{6×6} | | | | | | |

R = 1.0

 $H = [0]_{6 \times 6}$ $X_0^{\rm T} = [1.0 \quad 0.0 \quad 0.0 \quad 0.0 \quad 0.0]$

The computational results are given below where X_1, X_2 , and u are given. The values from the EISPAK program are given in the first column; the values from the algorithm are in the second column.

Table 3.1

Numerical Results for Example 1

| x ₁ | | | X. | 2 | u | |
|----------------|-----------|-----------|-----------|-----------|-----------|----------|
| t | EISPAK | algorithm | EISPAK | algorithm | EISPAK | algorith |
| 0.2 | 0.84040 | 0.84040 | 0.099001 | 0.099001 | -1.3221 | -1.3221 |
| 2.0 | 0.022247 | 0.022247 | 0.4430 | 0.4430 | -0.39998 | -0.39998 |
| 4.0 | -0.16908 | -0.16908 | 0.32909 | 0.32909 | -0.021178 | -0.02117 |
| 6.0 | -0.12993 | -0.12993 | 0.16242 | 0.16242 | 0.056753 | 0.05675 |
| 8.0 | -0.069071 | -0.069072 | 0.058280 | 0.058280 | 0.038792 | 0.03884 |
| 10.0 | -0.040360 | -0.041177 | 0.0043283 | 0.0043727 | 0.6605-02 | -0.357-0 |

A system in which A is 9 \times 9 was selected as the second example.

| ſ | 0 | | 1 | 0 | 0 | 0 | 0 | 0 | 0 | | 0 |
|---------------------------|-----|------|-----|-------|-----------|------------------|---------------------|--------|----------------|-----------------|--------|
| | 0 | | 0 | 0.21 | .65 -0.03 | 356 0 | -0. | 0299 0 | -0. | 027 | 0 |
| | -0. | 0458 | 1 | -0.01 | .33 0.0 | 004 0 | 0. | 0006 0 | 0. | 0007 | 0 |
| | 0 | | 0 | 0 | 0 | 1 | 0 | 0 | 0 | | 0 |
| A= | 0 | | 0 | 0 | -29. | 81 -0. | 0546 0 | 0 | 0 | | 0 |
| | 0 | | 0 | 0 | 0 | 0 | 0 | 1. | 0 | | 0 |
| | 0 | | 0 | 0 | 0 | 0 | -16 | 9 -0 | .13 0 | | 0 |
| | 0 | | 0 | 0 | 0 | 0 | 0 | 0 | 0 | | 1 |
| Į | . 0 | | 0 | 0 | 0 | 0 | 0 | 0 | -33 | 34 . 3 · | -0.182 |
| $\mathbf{B}^{\mathbf{T}}$ | = | [0 | -1. | 138 | -0.0348 | 0 29 | .56 0 | 47.25 | 0 16. | .4] | |
| Q | = (| diag | [0 | 0.05 | 10-4 | 10 ⁻⁴ | 10 ⁻⁴ 10 | -4 10- | ⁴] | | |
| R | = | 1 | | | | | | | | | |

 $x_0^{\rm T} = [-4.0 -3.0 -2.0 -1.0 1.0 2.0 3.0 4.0 5.0]$

.

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The first two states and the control are given in Table 3.2.

Table 3.2

Numerical Results for Example 2

| | X | ζ., ΄ | X. | | u | | |
|------|---------|-----------------------|----------|-----------|----------|-----------|--|
| t | EISPAK | ¹ algorith | m EISPAK | algorithm | EISPAK | algorithm | |
| 0.2 | -4.4914 | -4.4914 | -1.9499 | -1.9499 | -4.6531 | -4.6531 | |
| 2.0 | -3.7688 | -3.7688 | 1.1625 | 1.1625 | -0.18305 | -0.18305 | |
| 4.0 | -2.4121 | -2.4121 | 0.19929 | 0.19929 | 0.40611 | 0.40611 | |
| 6.0 | -2.3989 | -2.3989 | -0.14663 | -0.14663 | 0.29003 | 0.29003 | |
| 8.0 | -2.6751 | -2.6751 | -0.12266 | -0.12266 | 0.10517 | 0.10517 | |
| 10.0 | -2.7900 | -2.7900 | 0.064273 | 0.064273 | 0.22-11 | 0.17-09 | |

Both problems were run on an IBM 360 Model 44 in double precision. The first problem required 77.1 seconds of execution time by the new algorithm versus 88.8 seconds with EISPAK. The program for the algorithm was not optimized.

CHAPTER IV

SOLUTION OF THE UNCOUPLED DISCRETE SYSTEMS

4.1 A Discrete Linear Regulator

This section considers a linear constant coefficient discrete system represented by

$$X_{K+1} = \phi X_{K} + BU_{K}$$
(4.1)

with the initial condition vector

$$X(0) = X_0, \qquad K = 0, 1, 2, \dots, N$$
 (4.1a)

where ϕ is the state transition matrix and N is assumed to be a fixed integer. The quadratic performance criterion is

$$J = \frac{1}{2} X_{N}^{T} H X_{N} + \frac{1}{2} \sum_{K=0}^{N-1} [X_{K}^{T} Q X_{K} + U_{K}^{T} R U_{K}]$$
(4.2)

where it is assumed that the weighting matrices Q and R are independent to stage K.

The Hamiltonian is formed by

$$H = \frac{1}{2} X_{K}^{T} Q X_{K} + \frac{1}{2} U_{K}^{T} R U_{K} + \lambda_{K+1}^{T} [\phi X_{K} + B U_{K}]$$
(4.3)

When the discrete maximum principle is applied, the optimal control is given by

$$U_{K} = -R^{-1}B^{T}\lambda_{K+1}$$

$$(4.4)$$

where $\boldsymbol{\lambda}_{K+1}$ is the costate vector which obeys the equation

$$\lambda_{\rm K} = Q X_{\rm K} + \phi^{\rm T} \lambda_{\rm K+1} \tag{4.5}$$

The boundary condition for the unspecified terminal states is given as

$$\lambda_{\rm N} = HX_{\rm N} \tag{4.6}$$

Equations (4.1), (4.4), and (4.5) represent a set of linear difference equations for an open-loop control.

The system matrix of the discrete Riccati equation has been introduced previously (Section 2.2). The matrix is formulated from the canonical forward equations instead of the conventional backward approach, but it will be shown in a later part of this chapter that both structures of the system matrix produce equivalent feedback gain matrices at each stage.

The equation can be solved for λ_{K+1} in terms of λ_K since the state transition matrix, \dot{z} , always has an inverse

$$\lambda_{K+1} = -\phi^{-T}QX_{K} + \phi^{-T}\lambda_{K}$$
(4.7)

Substituting (4.7) into (4.1), with the expression of optimal control in (4.4), yields this equation for the state vector.

$$X_{K+1} = (\phi + BR^{-1}B^{T}\phi^{-T}Q)X_{K} - BR^{-1}B^{T}\phi^{-T}\lambda_{K}$$
(4.7a)

Equations (4.7) and (4.7a) are the desired canonical state and costate difference equations for the discrete linear regulator. This set of coupled equations may be expressed in the following compact form:

$$\begin{bmatrix} X \\ \lambda \end{bmatrix}_{K+1} = H_{DR} \begin{bmatrix} X \\ \lambda \end{bmatrix}_{K}$$
(4.8)

where H_{DR} represents the forward system matrix associated with the coefficients of the discrete linear regulator so that

$$H_{DR} = \begin{bmatrix} \phi + BR^{-1}B^{T} \div^{-T}Q & -BR^{-1}B^{T}\phi^{-T} \\ & & \\ -\phi^{-T}Q & \phi^{-T} \end{bmatrix}$$
(4.8a)

4.2 The Riccati Equation for Discrete Optimal Feedback Gain

Several alternative, but equivalent, recursive relations have been derived to solve the set of discrete boundary value problems in Section 4.1. In general, a closed loop solution p_K is assumed as

$$\lambda_{\rm K} = P_{\rm K} X_{\rm K} \tag{4.9}$$

Substituting (4.4) and (4.9) into (4.1) and (4.5) to eliminate $\lambda_{\rm K}$ yields

$$X_{K+1} = \phi X_{K} - BR^{-1}B^{T}P_{K+1}X_{K+1}$$
(4.10)

and

$$P_{K}X_{K} = QX_{K} + \phi^{T}P_{K+1}X_{K+1}$$
(4.10a)

By solving for X_{K+1} and eliminating it, the following is obtained:

$$P_{K}X_{K} = QX_{K} + \phi^{T}P_{K+1}[I+BR^{-1}B^{T}P_{K+1}]^{-1}\phi X_{K}$$
(4.11)

from which

$$P_{K} = Q + \phi^{T} P_{K+1} [I + BR^{-1} B^{T} P_{K+1}]^{-1} \phi \qquad (4.11a)$$

or equivalently

$$P_{K} = Q + \phi^{T} [P_{K+1}^{-1} + BR^{-1}B^{T}]^{-1} \phi$$
 (4.11b)

The terminal condition for $\mathbf{P}_{\mathbf{K}}$ is provided by (4.6) and (4.9) so that

$$P_{N} = H$$
 (4.12)

Equations (4.11a) and (4.11b) are developed in the well known discrete matrix Riccati equation associated with discrete optimal controls.

Usually, the matrix Riccati equation is solved recursively backward in time, starting K=N to K=0, and the feedback gain matrix P_{K} is stored at each stage. From (4.10), the recursive equation for the closed-loop state vector is expressed in terms of the prestored gain.

$$X_{K+1} = (I + BR^{-1}B^{T}P_{K+1})^{-1} X_{K}$$
 (4.13)

The optimal control U_{K} is then obtained as

$$U_{K} = -R^{-1}B^{T}\phi^{-T}[P_{K}-Q]X_{K}$$
(4.13a)

or in terms of P_{K+1}

$$U_{K} = -R^{-1}B^{T}[P_{K+1}^{-1} + BR^{-1}B^{T}]^{-1} \phi X_{K}$$
(4.13b)

4.3

The Discrete Kalman Filter

The development of the discrete filter model may be given by the following set of first-order difference equations:

$$X_{K+1} = \phi X_{K} + \Gamma \omega_{K}$$
 $K = 0, ..., N-1$ (4.14)

where

$$E(X_0) = \overline{X}_0 \tag{4.14a}$$

$$E(\omega_{\rm K}) = 0 \tag{4.14b}$$

$$E(x_0 - \overline{x}_0) (x_0 - \overline{x}_0)^T = P_0$$
 (4.14c)

$$E(\omega_{i}, \omega_{j}^{T}) = Q_{ij} \qquad (4.14d)$$

$$E(\omega_{\rm K})({\rm X}_0 - {\rm \overline{X}}_0)^{\rm T} = 0$$
 (4.14e)

Measurements \mathbf{Z}_{K} are made at stage K, and are related to the state \mathbf{X}_{K} by

$$Z_{K} = HX_{K} + V_{K}$$
 $K = 0, ..., N$ (4.15)

where

$$E(V_{K}) = 0$$
 (4.15a)

$$E(V_{i}V_{j}^{T}) = R_{ij}$$
(4.15b)

$$E(\omega_{i}V_{j}^{T}) = 0 \qquad (4.15c)$$

$$E(X_0 - \overline{X}_0)V_K^T = 0$$
 (4.15d)

It is assumed that the state transition matrix ϕ , input noise ω , system noise Q, and observation noise R are independent of stage K.

Numerous studies are available concerning least-square curve fitting, variational techniques, and maximum likelihood estimations to deal with the filtering problems. In cases where an additive input noise $w_{\rm K}$, as well as the output measurement error $V_{\rm K}$ exist, variable approaches have resulted in the following sets of estimation equations from either deterministic or statistical considerations.

The optimum state estimate X_{K+1} satisfies

$$X_{K+1} = \phi X_{K} + P_{K+1} H^{T} R^{-1} (Z_{K+1} - H \phi X_{K})$$
 (4.16)

and the equation for the covariance of the estimation error ${\rm P}_{\rm K+1}$ is

$$P_{K+1} = M_{K+1} - M_{K+1} H^{T} [HM_{K+1} H^{T} + R]^{-1} HM_{K+1}$$
(4.16a)

where M_{K+1} is defined by

$$M_{K+1} = \phi P_K \phi^T + \Gamma Q T^T$$
 (4.16b)

The initial conditions are

 $X(K_0) = X_0$ (4.16c)

and $P(K_0) = P_0$ (4.16d)

As shown in (4.16a) and (4.16b), P_{K} is independent of the measurement Z_{K} ; thus, the covariance matrix can be precomputed and stored to carry out the computation of the updated estimate in (4.16) with the current measurement.

In the case where c, P, R, Q, and H are all constant matrices, the filtering process may reach a steady state in the sense that M_{K} and P_{K} become constant matrices, M and P, as $K \rightarrow \infty$. The two matrix equations for determining M and P are

$$P^{-1} = M^{-1} + H^{T} R^{-1} H$$
(4.17)

or
$$P = M - MH^{T} (R+HMH^{T})^{-1} HM$$
 (4.17a)

and
$$M = \phi P \phi^{T} + \Gamma Q \Gamma^{T}$$
 (4.17b)

An algebraic nonrecursive expression for P_K is derived in Section 4.4. The new technique based on the uncoupling algorithm developed in Section 2.2 provides the determination of the transient solution at any particular stage without accumulating iteration from a given starting value. Furthermore, the steady-state solution is immediate and does not require the information about the eigenvalue and eigenvector of the system.

4.4 Reduced Discrete Linear Systems

In Section 3.3, a linear regulator problem was solved when the set of continuous system equations was coupled. An analogous technique to the continuous case is developed for a solution to a discrete linear regulator. An uncoupling algorithm for canonical system matrices associated with the discrete optimal controls and the Kalman filters has been previously discussed in detail. An algebraic expression for the solution matrix to a Riccati difference equation is presented as a subsidiary of the procedure.

The coupled set of difference equations for the optimization of the discrete linear regulator was derived in Section 4.2

$$\begin{bmatrix} X \\ \lambda \end{bmatrix}_{K+1} = H_{DR} \begin{bmatrix} X \\ \lambda \end{bmatrix}_{K}$$
(4.18)

The uncoupling of (4.18) may be preceded by introducing a set of new vectors \boldsymbol{Y}_{K} and $\boldsymbol{\omega}_{K}$ by the relation

$$\begin{bmatrix} X \\ \lambda \end{bmatrix}_{K} = \overline{V} \begin{bmatrix} Y \\ \omega \end{bmatrix}_{K} = \begin{bmatrix} V_{11} & V_{12} \\ V_{21} & V_{22} \end{bmatrix} \begin{bmatrix} Y \\ \omega \end{bmatrix}_{K}$$
(4.19)

where the transformation matrix \overline{V} has the structure given by (2.19a). Substituting (4.19) for (4.18) and premultiplying both sides by V^{-1} gives

$$\begin{bmatrix} \mathbf{Y} \\ \mathbf{\omega} \end{bmatrix}_{\mathbf{K}+1} = \bar{\mathbf{V}}^{-1} \mathbf{H}_{\mathbf{D}\mathbf{R}} \bar{\mathbf{V}} \begin{bmatrix} \mathbf{Y} \\ \mathbf{\omega} \end{bmatrix}_{\mathbf{K}}$$
(4.20)

Using the result of the uncoupling algorithm developed in Section 2.4, it follows that the uncoupled system equations for the discrete linear regulator will be

$$\begin{bmatrix} \mathbf{Y} \\ \mathbf{\omega} \end{bmatrix}_{\mathbf{K}+1} = \begin{bmatrix} \mathbf{H}_{\mathrm{D1}} & \mathbf{0} \\ \mathbf{0} & \mathbf{H}_{\mathrm{D1}}^{-\mathrm{T}} \end{bmatrix} \begin{bmatrix} \mathbf{Y} \\ \mathbf{\omega} \end{bmatrix}_{\mathbf{K}}$$
(4.20a)

The solution vectors for (4.20a) are then obtained as

$$Y_{K} = \phi_{11}(K_{0}, K)Y_{0}$$
(4.21)

and

$$\omega_{\rm K} = \phi_{22}({\rm K}_0, {\rm K})\omega_0 \tag{4.21a}$$

The uncoupled system equations in (4.21) and (4.21a) adjoin each other and have a set of properties which are directly analogous to the properties listed for a continuous system in Section 3.3.

The transition matrices $\dot{\circ}_{11}$ and ϕ_{22} have the relationship

$$\phi_{11}(K_0, K) = [\phi_{22}^{-1}(K_0, K)]^T$$
(4.22)

where

$$\phi_{ll}(K_0, K) = H_{Dl}^{K}$$
 (4.22a)

and

$$\phi_{22}(K_0, K) = (H_{D1}^{-T})^K$$
 (4.22b)

In a development similar to the continuous case, the unknown initial conditions Y_0 and w_0 can be determined by the use of (4.19) and the terminal condition given by (4.6).

$$V_{21}Y_{N} + V_{22}\omega_{N} = H[Y_{11}Y_{N} + V_{12}\omega_{N}]$$
(4.23)

Solving for \textbf{Y}_{N} yields

$$Y_{N} = \overline{H}\omega_{N}$$
 (4.23a)

where H is a final-value weighting matrix for the uncoupled system and is provided by

$$\overline{H} = [V_{21} - HV_{11}]^{-1} [HV_{12} - V_{22}]$$
(4.23b)

Considering the solution vectors Y_{K} and ω_{K} at final stage N, a constant factor between uncoupled initial conditions is determined from (4.23a).

$$Y_0 = S_0 \omega_0$$
 (4.24)

where

$$S_0 = \overline{H}_{D1}^{-N}\overline{H} (H_{D1}^{-N})^{T}$$
(4.24a)

Then Y_0 and ω_0 may be obtained in terms of the given value X_D

$$\omega_0 = (V_{11}S_0 + V_{12})^{-1} X_0$$
 (4.25)

and

$$Y_0 = S_0 \omega_0$$
 (4.25a)

Since S_0 can be calculated so that the N powers of H_{D1}^{-1} can be built up by squaring H_{D1}^{-1} and squaring the results, etc., the new initial conditions do not cause computational difficulties.

At each stage, the desired solution vectors for the coupled system can be reconstructed using the relation in (4.19).

$$\begin{bmatrix} X \\ \lambda \end{bmatrix}_{K} = \begin{bmatrix} V_{11} & V_{12} \\ V_{21} & V_{22} \end{bmatrix} \begin{bmatrix} H_{D1}^{K} & 0 \\ 0 & (H_{D1}^{-T})^{K} \end{bmatrix} \begin{bmatrix} Y_{0} \\ \omega_{0} \end{bmatrix}$$

$$= \begin{bmatrix} V_{11} & V_{12} \\ V_{21} & V_{22} \end{bmatrix} \begin{bmatrix} H_{D1}^{-(N-K)} \overline{H} (H_{D1}^{-N})^{T} & 0 \\ 0 & (H_{D1}^{-T})^{K} \end{bmatrix} \begin{bmatrix} \omega_{0} \\ \omega_{0} \end{bmatrix}$$

$$(4.26)$$

Since the eigenvalues of the submatrix H_{D1} are located outside the unit circle and the elements of (4.26) have only negative powers of H_{D1} , the expression in (4.26) will be stable numerically throughout the whole stages.

For convenient reference, the necessary computational procedures, similar to those previously outlined in Section 3.2, are summarized in the following steps:

- a) Obtain the set of difference equations in (4.1) and
 (4.5) and construct the system matrix H_{DR}.
- b) Use the sign algorithm for a discrete system outlined in Section 2.4 to obtain the transformation matrix V and \overline{V} .
- c) Compute Nth power of subblock H_{Dl} where N is the terminal time stage.
- d) Obtain \overline{H} given by (4.25b).
- e) Compute S using (4.24a).
- f) Compute initial conditions for uncoupled system.
- g) Reconstruct the desired solution vectors X_{K} and λ_{K} by (4.26).

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4.5 An Algebraic Solution for a Discrete Riccati Equation

It has been reported that an algebraic solution to the discrete Riccati equation can be obtained by use of the eigenvalues and eigenvectors of the system matrix [45]. A non-recursive expression for a solution matrix P_K made it possible to determine the steady-state solution of the Riccati equation as well as the transient solution at any particular time stage without iteration. The method reported, although conceptually simple, is not suitable for this study because of the complexity of finding the associated eigenvalues and eigenvectors.

In this section, a new procedure is presented which does not require either the iterational process or the burden of finding eigenvalues and eigenvectors. An algebraic expression for a feedback gain matrix of a discrete linear regulator is developed from the results described in Section 4.3. In (4.9) and (4.19),

$$V_{21}Y_{K}+V_{22}\omega_{K} = P_{K}(V_{11}Y_{K}+V_{12}\omega_{K})$$
(4.27)

Using the solution vectors in (4.21) and (4.21a), a non-recursive expression is derived for P_{K} as follows:

$$P_{K} = (V_{21}\phi_{11}S_{0} + V_{22}\phi_{22}) (V_{11}\phi_{11}S_{0} + V_{12}\phi_{22})^{-1}$$
(4.28)

From (2.28), it can be shown that

$$\lim_{\substack{N, K \to \infty \\ K < N}} P_{22} V_{12}^{-1} = T_2^{-1} = M_{22} M_{12}^{-1}$$
(4.29)

since

$$\lim_{\substack{N, K \to \infty \\ K \le N}} S_0 = 0$$
 (4.29a)

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The result of (4.29) is a steady-state solution consisting of eigenvectors of the system matrix corresponding to these eigenvalues which lie inside the unit circle.

A similar approach provides a nonrecursive solution for an error covariance matrix in the discrete Kalman filter. Since the initially known error covariance matrix in (4.16d) is dual to the terminal condition of the linear regulator given by (3.8c), the relation between the uncoupled initial vector is also dual in integration time.

From (4.9) and (4.19),

$$V_{21}Y_0 + V_{22}\omega_0 = P_0[V_{11}Y_0 + V_{12}\omega_0]$$
(4.30)

Assuming that

$$\omega_0 = S_0 Y_0 \tag{4.30a}$$

then

$$S_0 = -[V_{22} - P_0 V_{12}]^{-1} [V_{21} - P_0 V_{11}]$$
(4.30b)

The linear relation between solution vectors \textbf{Y}_{K} and $\boldsymbol{\omega}_{K}$ can be written

$$\omega_{\rm K} = S_{\rm K} Y_{\rm K} \tag{4.31}$$

where

$$S_{K} = (H_{D1}^{-T})^{K} S_{0} H_{D1}^{-K}$$
 (4.31a)
Substituting (4.19) and (4.31) for (4.9) yields

$$P_{K} = [V_{21} + V_{22}S_{K}] [V_{11} + V_{12}S_{K}]^{-1}$$
(4.32)

Equations (4.30b), (4.31a), and (4.32) constitute the desired nonrecursive algebraic solution for the error covariance matrix P_{K} . At any particular K, P_{K} can be obtained only by computing K powers of H_{DL}^{-1} .

The steady-state solution P is obtained by letting $K \rightarrow \infty$.

$$P_{\infty} = \lim_{K \to \infty} P_{K} = V_{21} V_{11}^{-1} = T = M_{21} M_{11}^{-1}$$
(4.33)

since H_{D1} corresponds to the eigenvalues outside the unit circle and S_{K} contains only negative powers of H_{D1} ,

$$S_{\infty} = \lim_{K \to \infty} S_{K} = \lim_{K \to \infty} (H_{D1}^{-T})^{K} S_{0} H_{D1}^{-K} = 0$$
(4.33a)

The steady-state solution derived in (4.33) is analogous to that of the continuous Riccati equation reported earlier [27,33].

4.6 Examples

4.6.1 Uncoupling Procedure for the Solution of a Discrete System

The uncoupled discrete obtained from Section 2.6.2 is solved completely by the outlined procedure in Section 4.4. Initial conditions and the terminal weighting matrix of the original problem are given as

$$X_0 = [-2.0 -1.0 2.0]^{T}$$
,

$$H = \begin{bmatrix} 0.5 & 0.1 & 0.3 \\ 0.1 & 0.2 & 0.6 \\ 0.3 & 0.6 & 0.8 \end{bmatrix} \text{ and } N = 20.$$

The initial vectors for the reduced system are calculated as

$$Y_0 = [-0.3722 - 17 \quad 0.4568 - 17 \quad 0.3241 - 17]^T$$

and $W_0 = [3.1803 \quad 15.508 \quad -4.0186]^T$

The desired optimal states and optimal controls for the coupled system are tabulated in Table 4.1.

Table 4.1

Optimal States and Controls for a Discrete Linear Regulator

| K | X _{lK} | x _{2K} | x _{3K} | U _K |
|----------------|---------------------------------------|---------------------------------------|---------------------------------------|------------------------------------|
| 1 | 1.3904 | -0.6096 | -3.6952 | 1.6952 |
| 2 | -4.7513 | 1.2487 | 1.8517 | -3.0709 |
| 3 | -0.8559 | 0.1920 | 0.5497 | 1.9477 |
| 4 | 0.1830 | -0.6054-01 | -0.1354 | 0.5195 |
| 5 | -0.6955-01 | 0.1827-01 | 0.5196-02 | -0.1263 |
| 10 | -0.1939-03 | 0.4172-04 | 0.1495-03 | 0.6260-03 |
| 15 | 0.3686-06 | -0.1050-06 | -0.4741-06 | -0.6190-06 |
| 20 | -0.1410-06 | -0.5022-07 | -0.1043-06 | -0.3052-07 |
| 10 15 20 | -0.1939-03 0.3686-06 -0.1410-06 | 0.4172-04 -0.1050-06 -0.5022-07 | 0.1495-03 -0.4741-06 -0.1043-06 | 0.6260-0 -0.6190-0 -0.3052-0 |

4.6.2 Solution for a Discrete Riccati Equation of Error Co-

variance

An initial navigation problem from Mehra [30] is adopted as a numerical example. The discrete Kalman filter is constructed from the system whose coefficient matrices are

$$\phi = \begin{bmatrix} 0.75 & -1.75 & -0.3 & 0 & -0.15 \\ 0.09 & 0.91 & -0.0015 & 0 & -0.008 \\ 0 & 0 & 0.95 & 0 & 0 \\ 0 & 0 & 0 & 0.55 & 0 \\ 0 & 0 & 0 & 0 & 0.905 \end{bmatrix}$$

$$\Gamma = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 \\ 24.64 & 0 & 0 \\ 0 & 0.835 & 0 \\ 0 & 0 & 1.83 \end{bmatrix} \quad H = \begin{bmatrix} 1 & 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 1 & 0 \end{bmatrix}$$
$$Q = \begin{bmatrix} 0.25 & 0 & 0 \\ 0 & 0.5 & 0 \\ 0 & 0 & 0.75 \end{bmatrix} \quad R = \begin{bmatrix} 0.4 & 0 \\ 0 & 0.6 \end{bmatrix}$$

and the initial error covariance matrix is given

| | -0.1 [.] | 0.2 | 0.3 | 0.4 | ך0.5 |
|---------|-------------------|-----|-----|-----|------|
| | 0.2 | 0.1 | 0.2 | 0.3 | 0.4 |
| $P_0 =$ | 0.3 | 0.2 | 0.1 | 0.2 | 0.3 |
| | 0.4 | 0.3 | 0.2 | 0.1 | 0.2 |
| | L0.5 | 0.4 | 0.3 | 0.2 | 0.1 |

Two programs were used to calculate the error covariance matrix, one based on the new non-recursive technique in Section 4.5 and the other based on the conventional recursive solution of the associated discrete Riccati equation. The results from both methods are compared to show the maximum error in the 12th and 13th significant digits in double precision on the IBM 360-44. The diagonal elements of the computed P_K are presented in Table 4.2.

Table 4.2

| K | P ₁₁ (K) | P ₂₂ (K) | Р ₃₃ (К) | P ₄₄ (K) | Р ₅₅ (К) |
|----|---------------------|---------------------|---------------------|---------------------|---------------------|
| 1 | -0.4949 | -0.11372 | 151.67 | 0.30929 | 2.3724 |
| 5 | 24.038 | 0.21626 | 310.28 | 0.42450 | 6.8506 |
| 10 | 24.741 | 0.66461 | 320.13 | 0.46808 | 8.1641 |
| 15 | 24.810 | 0.68089 | 321.32 | 0.47168 | 8.2999 |
| 20 | 24.821 | 0.68212 | 321.33 | 0.47174 | 8.3214 |
| 25 | 24.822 | 0.68231 | 321.34 | 0.47176 | 8.3219 |
| 30 | 24.822 | 0.68232 | 321.34 | 0.47176 | 8.3220 |

Solution Matrix of a Discrete Riccati Equation

Table 4.2 shows the convergence of P_K to the steady-state solution with increasing K. The steady-state solution for the Riccati equation is obtained from the partitions of the transformation matrix used; i.e.,

.

$$P_{\infty} = V_{21}V_{11}^{-1} = \begin{bmatrix} 24.822 & 1.6052 & -59.609 & -0.21033 & -6.9568 \\ 1.6052 & 0.68232 & -3.2971 & -0.16927 & -1.5205 \\ -59.609 & -3.2971 & 321.34 & 0.67997 & 9.122 \\ -0.21033 & -0.16927 & 0.67997 & 0.47176 & 0.26422 \\ -6.9568 & -1.5205 & 9.122 & 0.26422 & 8.322 \end{bmatrix}$$

•

CHAPTER V

NUMERICAL INTEGRATION OF A STIFF SYSTEM

5.1 The Set of Uncoupled Differential Equations

A new algorithm is developed for the numerical integration of linear stiff systems with constant coefficients having eigenvalues which differ greatly in magnitude. The intermediate size eigenvalues which may still be troublesome in either of the two sets are brought into consideration. When the new algorithm of the matrix filter generation in Section 2.5 is applied, the resulting state equations are completely uncoupled, and standard integration techniques can be utilized.

The differential equations for the eigenvalue subset matrices can now be generated by considering the first-order differential equations

$$X(t) = AX(t) + Bf(t)$$
 (5.1)

with initial conditions

 $X(t_0) = X_0$ (5.1a)

It is assumed that the eigenvalues in the same order of magnitude are isolated into subsets and X_1, \ldots, X_k are the corresponding uncoupled state vectors

$$X(t) = X_1(t) + X_2(t) + \dots + X_k(t)$$
 (5.2)

where *l* is the number of filters or subsets.

In addition, S_i denotes a matrix filter of the order $n \times n$

generated from the algorithm in Section 2.5.

$$S_{i} = M \begin{bmatrix} 0 & 0 & \cdot & \cdot & 0 \\ 0 & 0 & \cdot & \cdot & 0 \\ \cdot & \cdot & I & \cdot & 0 \\ \cdot & 0 & \cdot & \cdot & \cdot \\ \cdot & 0 & \cdot & \cdot & 0 \end{bmatrix} M^{-1}$$
(5.3)

where the partitioned identity matrix is located at the ith column and row and where

$$\sum_{i=1}^{\ell} S_i = I$$
 (5.4)

The vectors $X_{i}(t)$ in (5.2) then become

$$X_{i}(t) = S_{i}X(t)$$
 (5.5)

so that

. .

$$X(t) = \sum_{i=1}^{\ell} X_{i}(t) = \sum_{i=1}^{\ell} S_{i}X(t)$$
 (5.6)

To derive the desired differential equations in uncoupled form, the first differentiated equation (5.5) with respect to t is

$$\dot{x}_{i}(t) = S_{i}X(t) = S_{i}[AX(t) + Bf(t)]$$
 (5.7)

The matrix S. will commute with A, thus

$$X_{i}(t) = AS_{i}X(t) + S_{i}Bf(t)$$
 (5.7a)

which finally gives

.
$$X_{i}(t) = AX_{i}(t) + S_{i}Bf(t)$$
 (5.7b)

The terms of (5.7b) are multiplied through by the identity matrix, and (5.4) is used along with (5.5) to simplify as shown below:

$$\dot{X}_{i}(t) = A\left(\sum_{i=1}^{2} S_{i}\right)X_{i}(t) + S_{i}Bf(t)$$

$$= AS_{i}X_{i}(t) + A\left(\sum_{\substack{j=1\\ j\neq i}}^{2} S_{j}\right)X_{i}(t)X(t) + S_{i}Bf(t)$$

$$= AS_{i}X_{i}(t) + A\left(\sum_{\substack{j=1\\ j\neq i}}^{2} S_{j}\right)S_{i}(t) + S_{i}Bf(t) \quad (5.8)$$

Since $S_{i}(t)S_{i}(t) = 0$ for all $j \neq i$, then

$$\dot{X}_{i}(t) = S_{i}AX_{i}(t) + S_{i}Bf(t)$$

$$= A_{i}X_{i}(t) + S_{i}Bf(t)$$
(5.8a)

Equation (5.8a) is the desired uncoupled differential equation, and the eigenvalues are completely isolated into the subsystem matrix A_i .

The initial conditions for (5.8a) are developed from (5.5)

 $X_{i}(0) = S_{i}X(0)$ (5.8b)

The integration step size for each uncoupled state equation is determined in the usual manner.

Since $|R_e^{\lambda_1}| < |R_e^{\lambda_2}| < \ldots < |R_e^{\lambda_n}|$, the step size can be changed accordingly for each subset. The step size can be selected by taking the average trace for each subset matrix A_i .

5.2 Examples

For the first example, a simple network analysis problem given by Lee was selected and compared [26]. The state equations to be integrated are

$$\begin{bmatrix} x_{1}(t) \\ \vdots \\ x_{2}(t) \end{bmatrix} = \begin{bmatrix} -1000 & 0 \\ 2000 & -1 \end{bmatrix} \begin{bmatrix} x_{1}(t) \\ x_{2}(t) \end{bmatrix} + \begin{bmatrix} 1 \\ 0 \end{bmatrix} f(t)$$

and the initial conditions are given as

$$\begin{bmatrix} x_{1}(0) \\ x_{2}(0) \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

where

$$\mathbf{X} = \begin{bmatrix} \mathbf{X}_{1} \\ \mathbf{X}_{2} \end{bmatrix} \mathbf{A} = \begin{bmatrix} -1000 & 0 \\ 0 \\ 2000 & -1 \end{bmatrix} \mathbf{B} = \begin{bmatrix} 1 \\ 0 \end{bmatrix} \mathbf{f}(\mathbf{t}) = \mathbf{I}(\mathbf{t})$$

The eigenvalues of A are $\lambda_1 = -1000$ and $\lambda_2 = -1$, thus widely spaced. The step size was taken to be $h_1 = \frac{1}{5\lambda_1} = 0.0002$ during the transient time period due to a large eigenvalue, then changed to $h_2 = \frac{1}{5\lambda_2} = 0.2$ for the subset of small eigenvalues.

The integration interval is taken to be 0<t<5, and 75 integration steps were used. The high-and low-pass matrices generated by the algorithm developed in Section 2.5 are

$$S_{HP} = \begin{bmatrix} 1.00000000 & -0.617958115 - 17 \\ -2.002002002 & -0.5551115123 - 14 \end{bmatrix}$$

and

$$S_{LP} = \begin{bmatrix} -0.1110223023-15 & 0.6179585115-17^{-1} \\ 2.002002002 & 1.00000000 \\ 1.000000000 & -1 \end{bmatrix}$$

For the purpose of comparison, the matrix filters constructed from the Butterworth function are presented.

$$S_{HP} = \begin{bmatrix} 1 & 0 \\ -2.00200203 & 1.0-8 \end{bmatrix}$$

and

$$S_{LP} = \begin{bmatrix} -1.0000002 - 16 & 0 \\ 2.00200203 & 1.0000001 \end{bmatrix}$$

The solution vector X_2 for a high-pass matrix are compared in Table 5.1

Table 5.1

Solution Vector X_2 for a High-Pass Matrix

| Integ Step | y t | Conventional Filter Theory | New Algorithm | Exact X ₂ |
|---------------|--------|-------------------------------|----------------|----------------------|
| 0 | 0.0 | 0.0 | 0.0 | 0.0 |
| 10 | 0.002 | 2.26895019E-03 | 2.268942174-03 | 2.69894021E-03 |
| 20 | 0.004 | 6.02667963E-03 | 6.026679269-03 | 6.02670013E-03 |
| 30 | 0.006 | 9.97900485E-03 | 9.979008405-03 | 9.97900962E-03 |
| 40 | 0.008 | 1.39507856E-02 | 1.395079204-02 | 1.39507949E-02 |
| 50 | 0.01 | 1.79183299E-02 | 1.791834164-02 | 1.79183483E-02 |
| *55 | 1.01 | 1.27082125E00 | 1.270821384E00 | 1.27083286E00 |
| 60 | 2.01 | 1.73174577E00 | 1.731745951E00 | 1.73175437E00 |
| 65 | 3.01 | 1.90131311E00 | 1.901313295E00 | 1.90131793E00 |
| 70 | 4.01 | 1.96369442E00 | 1.963694618E00 | 1.96369389E00 |
| 75 | 5.01 | 1.98664358E00 | 1.986643786E00 | 1.98664483E00 |

*Step size changed after 50th step

For the second example, a 4 x 4 matrix with widely spaced eigenvalues was selected to illustrate the procedure of the bandpass filter algorithm. The state equation was assumed to be of the form $\dot{x}(t) = Ax(t)$ where $A = MAM^{-1}$ with

 $\Lambda = \text{diag}[-1200 -500 -1.5 -0.5]$

anđ

| | | | 1 | 2 | 3 7 | |
|---|----|-------|---|---|-----|---|
| м | == | 1 | 1 | 2 | 3 | |
| | | 2 | 2 | 2 | 3 | |
| | | L_2 | З | З | 3 | ļ |

which gives

| | └ -1.493+03 | 1.99+03 | -1.988+03 | ך 9.93+02 |
|-----|--------------------|-----------|-----------|------------|
| λ = | 2.106+03 | -1.609+03 | 1.6105+03 | -1.406+03 |
| ** | 4.206+03 | -3.209+03 | 3.2105+03 | -2.806+03 |
| | L 2.710+03 | -1.215+03 | 1.218+03 | -1.8105+03 |

The initial conditions are given as

 $x^{T}(0) = [2 1 -1 -2]$

The eigenvalues were isolated so that $\lambda = -1200$ was contained in the high-pass filter, $\lambda = -500$ in the band-pass filter, and the remaining two in a low-pass filter. The submatrices for the uncoupled state equations are given below

$$A_{1} = \begin{bmatrix} 7.0 & -10.0 & 12.0 & -7.0 \\ 6.0 & -9.0 & 10.5 & -6.0 \\ 6.0 & -9.0 & 10.5 & -6.0 \\ 10.5 & -15.0 & 18.0 & -10.5 \end{bmatrix}$$

$$A_{2} = \begin{bmatrix} -.15E+04 & .20E+04 & -.20E+04 & .10E+04 \\ -.15E+04 & .20E+04 & -.20E+04 & .10E+04 \\ -.30E+04 & .40E+04 & -.40E+04 & .20E+04 \\ -.45E+04 & .60E+04 & -.60E+04 & .30E+04 \end{bmatrix}$$

and

$$A_{3} = \begin{bmatrix} .0 & .0 & .0 & .0 \\ .36E+04 & -.36E+04 & .36+04 & -.24E+04 \\ .72E+04 & -.72E+04 & .72+04 & -.48E+04 \\ .72E+04 & -.72E+04 & .72+04 & -.48E+04 \end{bmatrix}$$

Eighteen iterations were programmed in the sign algorithm. All calculations were in double precision on the UNIVAC 1108, and the filter matrices are correct to 16 digits which were presented in Chapter II. The trace of the matrices A_1, A_2 , and A_3 were -2.0, -500, and -1200, respectively. Integration step sizes of 0.05, 0.005, 0.0005 were used in a fourth-order Runge-Kutta algorithm to calculate $X_1(t)$, $X_2(t)$, and $X_3(t)$.

The calculated values for $X_1(t)$, $X_2(t)$ and $X_3(t)$ are given in Tables 5.2 through 5.4 where $X_i^T(t) = [X_{1i}, X_{2i}, X_{3i}, X_{4i}]$.

| T | ab | 1 | е | 5 | ٠ | 2 |
|---|----|---|---|---|---|---|
| | | | | | | |

| | | 4 | | |
|---|---------------------|---------------------|---------------------|---------------------|
| t | X ₁₁ (t) | X ₂₁ (t) | X ₃₁ (t) | x ₄₁ (t) |
| 0 | 0 | 0 | 0 | 0 |
| 1 | 2.30040 | 4.11999 | 4.11999 | 3.45060 |
| 2 | 1.90855 | 3.01219 | 3.01219 | 2.86283 |
| 3 | 1.27212 | 1.94151 | 1.94151 | 1.90819 |
| 4 | 0.79714 | 1.20314 | 1.20314 | 1.19570 |
| 5 | 0.48919 | 0.73545 | 0.73545 | 0.73379 |

Solution Vector X1(t) for a Low-Pass Matrix

Table 5.3

| t | X ₁₂ (t) | X ₂₂ (t) | X ₃₂ (t) | x ₄₂ (t) |
|------|---------------------|---------------------|---------------------|---------------------|
| 0 | 2 | 2 | 4 | 6 |
| 0.01 | 0.55373E-02 | 0.55373E-02 | 0.11074E-01 | 0.16611E-01 |
| 0.02 | 0.15331E-04 | 0.15331E-04 | 0.30662E-04 | 0.45993E-04 |
| 0.03 | 0.42446E-0 | 0.42446E-07 | 0.84892E-07 | 0.12733E-06 |
| 0.04 | 0.11751E-09 | 0.11751E-09 | 0.23503E-09 | 0.35254E-09 |
| 0.05 | 0.32082E-12 | 0.32054E-12 | 0.64165E-12 | 0.96076E-12 |
| | - | | - | - |
| 5 | -0.455E-14 | 0.482E-14 | -0.908E-14 | -0.153E-13 |

Solution Vector X2(t) for a Band-Pass Matrix

Table 5.4

Solution Vector X3(t) for a High-Pass Matrix

| t | X ₁₃ (t) | X ₂₃ (t) | x ₃₃ (t) | x ₄₃ (t) |
|--------|---------------------|---------------------|---------------------|---------------------|
| 0 | 0 | -4 | -8 | -8 |
| 0.0025 | -0.11E-16 | -0.19914 | -0.39829 | -0.39829 |
| 0.0050 | 0.45E-18 | -0.99149E-02 | -0.19829E-02 | -0.19829E-02 |
| 0.0075 | 0.10E-17 | -0.49363E-03 | -0.98726E-03 | -0.98726E-03 |
| 0.0100 | 0.10E-17 | -0.24576E-04 | -0.49153E-04 | -0.49153E-04 |
| 0.0125 | 0.10E-17 | -0.12235E-07 | -0.24471E-05 | -0.24471E-05 |
| 0.0150 | 0.10E-17 | -0.60918E-07 | -0.12183E-06 | -0.12183E-06 |
| 0.0175 | 0.10E-17 | -0.30329E-08 | -0.60658E-08 | -0.60658E-08 |
| 0.0200 | 0.10E-17 | -0.15100E-09 | -0.30200E-09 | -0.30200E-09 |

The solution vector $X(t) = X_1(t) + X_2(t) + X_3(t)$ is given in Table 5.4 and agrees with the exact solution to 10 digits for whole intervals $0 \le t \le 5$.

The exact solution is obtained from known eigenvalues and eigenvectors.

Table 5.5

| t | x ₁ | x ₂ | x ₃ | x ₄ |
|--------|----------------|----------------|----------------|----------------|
| 0 | 2 | 1 | -1 | -2 |
| 0.0025 | 0.58797 | 3.38504 | 3.75894 | 1.34318 |
| 0.0050 | 0.19403 | 3.17662 | 3.33087 | 0.51746 |
| 0.0075 | 0.09170 | 3.07998 | 3.12652 | 0.20712 |
| 0.0100 | 0.07288 | 3.05789 | 3.07134 | 0.12948 |
| 0.0125 | 0.07793 | 3.05924 | 3.06310 | 0.12268 |
| 0.0150 | 0.08977 | 3.06735 | 3.06692 | 0.13631 |
| 0.0175 | 0.10350 | 3.07736 | 3.07768 | 0.15572 |
| 0.0200 | 0.11772 | 3.08787 | 3.08796 | 0.17671 |
| 0.03 | 0.17469 | 3.13002 | 3.13002 | 0.26203 |
| 0.04 | 0.23061 | 3.17120 | 3.17120 | 0.34591 |
| 0.05 | 0.28540 | 3.21133 | 3.21133 | 0.42810 |
| | - | | 1 111 | |
| 1.0 | 2.30040 | 4.11999 | 4.11999 | 3.45060 |
| | - | | - | |
| 5.0 | 0.48919 | 0.73545 | 0.73545 | 0.73379 |

Solution Vector for $X(t) = X_1(t) + X_2(t) + X_3(t)$

It should be noted that the vectors $X_2(t)$ and $X_3(t)$ reach limiting values set by the elements in S_2 and S_3 which should be zero. This problem can be alleviated by setting all elements in S_i to zero when they are at machine limit.

CHAPTER VI

CONCLUSIONS

In this study, new algorithms for the integration of the coupled differential equations from the optimal control with quadratic criteria and optimal filtering have been developed.

The matrix sign function made it possible to uncouple the set of differential equations so that the resulting computations for the state transition matrix are of the order n/2 when the original system matrix A is of the order $n \times n$. The algorithm required two subblocks of state transition matrices to solve the general forms of system equations. However, certain important classes of system optimization problems require only one halfsized subblock due to the particular form of system coefficient matrices. This advantage saves considerable computational efforts particularly when the system order is high.

The new method permitted the state and costate equations from a quadratic linear regulator to be integrated simultaneously forward in time, thereby; the storage problem was overcome in calculating the feedback control law of the more conventional method.

Test problems have been made in several cases and results show a reduction in both the computation time and the size of the program required. The results of the new method show satisfactory agreement with solutions from the more common methods.

This study also developed a numerical integration technique suitable for the solution of stiff state equations by isolating the eigenvalues with large magnitude. Instead of dealing with the integration method itself, the new technique gradually reduced the stiffness during the integration process. This was accomplished by discarding the uncoupled solution set corresponding to the eigenvalues having the largest negative real parts as their contribution becomes negligible. The effect of the troublesome eigenvalues was therefore removed.

The sign of the complex eigenvalue space was shifted by adding δI to the system matrix A, and the matrix filters were generated. The amount of the shifting factor δ was selected to isolate the troublesome eigenvalues. The presence of eigenvalues with large negative real parts is readily recognized by observing the main diagonal of the matrix A, since the trace of A is the sum of the real part of the eigenvalues.

Filter matrices generated by the new algorithm uncoupled the solution sets to the accuracy attainable from the machine. The advantage of the band-pass filter was demonstrated in an example problem.

In this paper the uncoupling procedure has been applied only to the linear time-invariant case. The same approach could be extended to the time-varying and nonlinear stiff equations with an increased number of calculations. The generation of the filter matrix will be more complicated by periodically repeating the computation of a matrix sign function of a time-varying system matrix or the Jacobian matrix and the uncertainty of the selection of a shifting factor δ . This process should be undertaken whenever there is an abrupt change in the coefficients of the state equations.

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This work suggests further studies in the following areas:

- a) Extension of the sign algorithm to the time-varying matrix
- b) Application of the uncoupling algorithm to the system optimization with time-varying system coefficients
- c) Development of integration techniques to solve the time varying stiff equations using the matrix filter algorithm
- d) Improvement of the computation of the matrix sign function

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APPENDIX A

MATRIX SIGN FUNCTION

Consider a square matrix A of the order N and

$$A = M \Lambda M^{-1}$$
 (A.1)

where M is the eigenvector matrix of A. Suppose that p of the N eigenvalues are positive and n are negative so that p+n = N.

The matrix function sign A is defined by

sign A = M
$$\begin{bmatrix} I_{p \times p} & 0 \\ 0 & -I_{n \times n} \end{bmatrix} M^{-1}$$
 (A.2)

The sign A is calculated by the algorithm

$$(\text{sign A})^{i+1} = \frac{1}{2}(\text{sign A})^{i} + \frac{1}{2}((\text{signA})^{i})^{-1}$$
 (A.3)

with (sign A) 0 = A.

The iterative process is terminated when trace[(sign A)ⁱ⁺¹] = trace[(sign A)ⁱ] to the desired accuracy.

APPENDIX B

Asymptotic Solution of Riccati Equation Consider the Riccati equation

$$A + BP + PC + PDP = 0 \tag{B.1}$$

The matrix of coefficients takes the form

$$\overline{A} = \begin{bmatrix} B & A \\ -D & -C \end{bmatrix}$$
(B.2)

Let the Jordan form of \overline{A} be

$$\begin{bmatrix} M & M_{12} \\ 11 & M_{22} \end{bmatrix} \begin{bmatrix} \Lambda_1 & 0 \\ 0 & \Lambda_2 \end{bmatrix} = \begin{bmatrix} B & A \\ -D & -C \end{bmatrix} \begin{bmatrix} M_{11} & M_{12} \\ M_{21} & M_{22} \end{bmatrix}$$
(B.3)

Equating terms after the block multiplication gives

$$M_{11}\Lambda_{1} = BM_{11} + AM_{21} \qquad M_{12}\Lambda_{2} = BM_{12} + AM_{22}$$
$$M_{21}\Lambda_{1} = -DM_{11} - CM_{21} \qquad M_{22}\Lambda_{2} = -DM_{12} - CM_{22} \qquad (B.4)$$

Performing multiplications on both sides, assuming the M_{21}^{-1} and M_{22}^{-1} exist,

$$M_{11}\Lambda_{1}M_{21}^{-1} = BM_{11}M_{21}^{-1} + A$$

$$M_{11}\Lambda_{1}M_{21}^{-1} = -M_{11}M_{21}^{-1}DM_{11}M_{21}^{-1} - M_{11}M_{21}^{-1}C$$
(B.5a)

and

$$M_{12}\Lambda_2 M_{22}^{-1} = BM_{12}M_{22}^{-1} + A$$

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$$M_{12}\Lambda_2 M_{22}^{-1} = -M_{12}M_{22}^{-1}DM_{12}M_{22}^{-1} - M_{12}M_{22}^{-1}C$$
(B.5t)

Subtracting the lower equation from the upper in (B.5a) and (B.5b) gives

$$A+BM_{11}M_{21}^{-1}+M_{11}M_{21}^{-1}C+M_{11}M_{21}^{-1}DM_{11}M_{21}^{-1} = 0$$

$$A+BM_{12}M_{22}^{-1}+M_{12}M_{22}^{-1}C+M_{12}M_{22}^{-1}DM_{12}M_{22}^{-1} = 0$$
(B.6)

which are the Riccati equations with $P = M_{12}M_{21}^{-1}$ and $P = M_{12}M_{22}^{-1}$.