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Optimal Filtering Scheme for Bilinear Discrete-Time Systems: a Linear Matrix Inequality Approach

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Abstract: The filtering problem is among the fundamental issues in control and signal processing. Several approaches such as $H_2$ optimal filtering and $H_\infty$ optimal filtering have been developed to address this issue. While the optimal $H_2$ filtering problem has been extensively studied in the past for linear systems, to the best of our knowledge, it has not been studied for bilinear systems. This is indeed surprising, since bilinear systems are important class of nonlinear systems with well-established theories and applications in the variety of fields. The problem of $H_2$ optimal filtering for discrete-time bilinear systems is addressed in this paper. The filter design problem is formulated in the convex optimization framework using linear matrix inequalities. The results are used for the optimal filtering of a bilinear model of an electro-hydraulic drive.

1. INTRODUCTION

The filtering problem is among the fundamental problems in control theory and signal processing and therefore over the past it has received a lot of attention. Several approaches such as $H_2$ optimal filtering and $H_\infty$ optimal filtering have been developed to address this issue (Anderson and Moore [1979]). In general, there are two approaches to solve the filtering problem: the Riccati-like approaches and the linear matrix inequality (LMI) approach. Generally, the algorithms for optimal filtering of linear discrete-time systems which has been proposed in the past is based on the optimization of an $H_2$ norm (Anderson and Moore [1979]). This makes sense, because the statistical knowledge of the input signal, particularly a white-noise process, corrupting the measurement output is described as the sum of the output variances which leads to the $H_2$ norm. The necessary and sufficient conditions based on a Riccati filtering equation for the existence of an estimator structure associated with the first category were derived (Basar and Bernhard [1995], Petersen and McFarlane [1994]).

The focus of this paper is on the second category of the filtering techniques. An example of such filtering methods is the one proposed in Palhares and Peres [1998]. In Palhares and Peres [1998], the filtering problem has been cast in terms of linear matrix inequalities (LMI’s). In this framework, the global optimal solutions are attained through convex optimization procedures, which can be efficiently solved. The $H_2$ optimal filtering design was derived from the state-space definition of the $H_2$ norm of the transfer function which relates the noise signal to the estimation error.

Both families of the methods have been extended for robust filtering of linear systems (See e.g. Petersen and McFarlane [1996], Tuan et al. [2001], Gao et al. [2008]).

While the optimal $H_2$ filtering problem has been extensively studied in the past for linear systems, to the best of our knowledge, it has not been studied for bilinear systems. This is indeed surprising, since bilinear systems are important class of nonlinear systems with well established theories and applications. These systems are used in the variety of fields to describe the processes ranging from electrical networks, hydraulic systems to heat transfer, and chemical processes. Moreover, many highly nonlinear systems may be modeled as bilinear systems with appropriate state feedback or can be approximated as bilinear systems in the so-called bilinearization process. See e.g. Svoronos et al. [1980]. The problem of $H_2$ optimal filtering for discrete-time bilinear systems is addressed in this paper. The filter design problem is formulated in the convex optimization framework using linear matrix inequalities. This is an extension of the optimal filtering scheme in Palhares and Peres [1998], to support bilinear systems. The results are used for the optimal filtering of a bilinear model of an electro-hydraulic drive.

The notation used in this paper is as follows: $M^*$ denotes transpose of matrix if $M \in \mathbb{R}^{n \times m}$ and complex conjugate transpose if $M \in \mathbb{C}^{n \times m}$. The $Tr(M)$ denotes the trace of the matrix $M$. The $\otimes$ stands for the Kronecker Product. The standard notation $>\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\cdot\·
The observability gramian is dually obtained by:

$$Q := \sum_{i=1}^{\infty} \sum_{k_i=0}^{\infty} \cdots \sum_{k_1=0}^{\infty} Q_i^*, Q_i,$$

where:

$$Q_i(k_1) = CA^{k_1},$$

$$Q_i(k_1, \ldots, k_i) = \begin{bmatrix} Q_{i-1}N_1 \\ Q_{i-1}N_2 \\ \vdots \\ Q_{i-1}N_m \end{bmatrix} A^{k_i}.$$

If $A$ is stable, the gramians are given by the solutions of the generalized Lyapunov equations (Zhang et al. [2003] and Zhang and Lam [2002]):

$$APA^* - P + \sum_{j=1}^{m} N_j PN_j^* + BB^* = 0, \quad (4)$$

$$A^*QA - Q + \sum_{j=1}^{m} N_j^* QN_j + C^*C = 0. \quad (5)$$

These generalized Lyapunov equation (4) has a unique solution if and only if:

$$W = (A \otimes A - I + \sum_{j=1}^{m} N_j \otimes N_j)$$

is nonsingular. The dual condition can be found for (5). See (Zhang and Lam [2002]) for more details.

The generalized Lyapunov equations can be solved iteratively. The controllability gramian $P$ is obtained by (Zhang et al. [2003] and Zhang and Lam [2002]):

$$P = \lim_{i \to \infty} \tilde{P}_i,$$

where:

$$A\tilde{P}_i A^* - \tilde{P}_i + BB^* = 0,$$

$$A\tilde{P}_i A^* - \tilde{P}_i + \sum_{j=1}^{m} N_j \tilde{P}_{i-1} N_j^* + BB^* = 0, \quad i = 2, 3, \ldots \quad (8)$$

The observability gramian is dually obtained by:

$$Q = \lim_{i \to \infty} \tilde{Q}_i,$$

where:

$$A^*\tilde{Q}_i A - \tilde{Q}_i + C^*C = 0,$$

$$A^*\tilde{Q}_i A - \tilde{Q}_i + \sum_{j=1}^{m} N_j^* \tilde{Q}_{i-1} N_j + C^*C = 0, \quad i = 2, 3, \ldots \quad (10)$$

The controllability and observability gramians show how difficult a system is to control and to observe. The gramians for bilinear systems have an important property which will be used for $H_2$ filtering in the next section. For bilinear system $\Sigma$, if $A$ is stable and the reachability gramian $P$ (or observability gramian $Q$) exists; then its $H_2$ norm can be computed from (Zhang and Lam [2002]):

$$\|\Sigma\|_2 = \sqrt{Tr(CPC^*)} = \sqrt{Tr(B^*QB)} \quad (11)$$

3. $H_2$ OPTIMAL FILTERING

Consider the following bilinear time-invariant discrete-time system given by:

$$S : \begin{cases} x(k+1) = Ax(k) + \sum_{j=1}^{m} N_j x(k)u_j(k) + Bw(k), \\
y(k) = Cx(k) + Dw(k), \\
z(k) = Lx(k). \end{cases} \quad (12)$$

where $x(k) \in R^n$ is the state vector, $y(k) \in R^r$ is the measurements output vector, $w(k) \in R^m$ is the noise signal vector (including process and measurement noises), and $z(k) \in R^p$ is the signal to be estimated. It is assumed that $(A,C)$ is detectable. This guarantees that there exists an observer constant gain such that the filter is asymptotically stable. The goal is to design an asymptotically stable linear filter described by:

$$F : \begin{cases} \tilde{x}(k+1) = A\tilde{x}(k) + \sum_{j=1}^{m} N_j \tilde{x}(k)w_j(k) + \hat{K}(y(k) - CZ(k)), \\
\tilde{z}(k) = L\tilde{x}(k) \end{cases} \quad (13)$$

where $K \in R^n \times r$ is the filter constant gain to be determined.

The state error is defined as $e(k) := x(k) - \tilde{x}(k)$, then the dynamics of the estimation error is described by:

$$E : \begin{cases} e(k+1) := A_e e(k) + \sum_{j=1}^{m} N_j e(k)w_j(k) + B_e w(k), \\
\tilde{z}(k) = L_e(k). \end{cases} \quad (14)$$

where $z(k) := z(k) - \tilde{z}(k)$ is the estimation error, and:

$$A_e := A - KC, \\
B_e := B - KD. \quad (15)$$

In the optimal $H_2$ filtering scheme, a bilinear filter F needs to be determined such that the estimation error variance is minimized. The problem therefore will be:

$$\min_K \|E\|_2^2$$

The $H_2$ norm of estimation error dynamics according to (11) can be computed as:

$$\|E\|_2 = \sqrt{Tr(B_e^*Q_e B_e)} \quad (17)$$

where $Q_e$ is the observability gramian of the bilinear system (14) and is the solution to the generalized Lyapunov equation:

$$A_e^* Q_e A_e - Q_e + \sum_{j=1}^{m} N_j^* Q_e N_j + L^* L = 0 \quad (18)$$

The state error is defined as $e(k) := x(k) - \tilde{x}(k)$, then the dynamics of the estimation error is described by:

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$$A_e^* Q_e A_e - Q_e + \sum_{j=1}^{m} N_j^* Q_e N_j + L^* L = 0 \quad (18)$$
In the following some results are stated and proved which will be used later to reformulate our problem in LMI framework:

**Lemma 1.** Let $A$ be stable and $W$ which is defined as:

$$W = (A^* \otimes A^* - I + \sum_{j=1}^{m} N_j^* \otimes N_j^*)$$  \hspace{1cm} (19)

be nonsingular. If $X$ satisfies:

$$A^*X - X + \sum_{j=1}^{m} N_j^* X N_j \leq 0,$$  \hspace{1cm} (20)

then: $X \geq 0$.

**Proof:**

Let $X$ satisfies (20), there exist $M \geq 0$ for which:

$$A^*X - X + \sum_{j=1}^{m} N_j^* X N_j + M = 0,$$  \hspace{1cm} (21)

On the other hand, $A$ is stable and $W$ which is obtained by duality from (6) as:

$$W = (A^* \otimes A^* - I + \sum_{j=1}^{m} N_j^* \otimes N_j^*)$$

is nonsingular, The generalized Lyapunov equation (21) has a unique solution which is obtained as:

$$X = \lim_{i \to \infty} \tilde{X}_i,$$  \hspace{1cm} (22)

where:

$$A^*\tilde{X}_i A - \tilde{X}_i + M = 0,$$

$$A^*\tilde{X}_i A - \tilde{X}_i + \sum_{j=1}^{m} N_j^* \tilde{X}_{i-1} N_j + M = 0,$$  \hspace{1cm} (23)

Since $M \geq 0$, then $\tilde{X}_1 = \sum_{k=0}^{\infty} (A^k)MA^k \geq 0$. For $i = 2, 3, \ldots$, we have:

$$\sum_{j=1}^{m} N_j^* \tilde{X}_{i-1} N_j + M \geq 0,$$

consequently: $\tilde{X}_i \geq 0$. Therefore: $X = \lim_{i \to \infty} \tilde{X}_i \geq 0$.

**Proposition 2.** Let for bilinear system (1), $A$ be stable and $W$ which is defined as:

$$W = (A^* \otimes A^* - I + \sum_{j=1}^{m} N_j^* \otimes N_j^*)$$

be nonsingular. Assume that $Q$ is the observability gramian of (1). If $\tilde{Q}$ satisfies:

$$A^*\tilde{Q} A - \tilde{Q} + \sum_{j=1}^{m} N_j^* \tilde{Q} N_j + C^*C \leq 0$$  \hspace{1cm} (25)

then: $\tilde{Q} \geq Q$.

**Proof:**

Subtract (25) from (5) and apply Lemma 1 with $X = \tilde{Q} - Q$.

This proposition has an interesting consequence:

**Corollary 3.** Let $A_\psi$ be stable and $W_\psi$ which is defined as:

$$W_\psi = (A_\psi^* \otimes A_\psi^* - I + \sum_{j=1}^{m} N_j^* \otimes N_j^*)$$

is nonsingular. Let $Q_\psi$ be the observability gramian for the bilinear system (14) and assume that there exist $Q_\psi$ which satisfies:

$$A_\psi^*Q_\psi A_\psi - Q_\psi + \sum_{j=1}^{m} N_j^* Q_\psi N_j + L^*L \leq 0,$$  \hspace{1cm} (27)

then:

$$Tr(B_\psi^*Q_\psi B_\psi) \geq Tr(B_\psi^*Q_\psi B_\psi).$$  \hspace{1cm} (28)

In the following, the $H_2$ optimal filtering problem for bilinear system is cast as a convex optimization problem:

**Theorem 4.** Consider the following optimization problem:

$$\min_{Y, V} \text{Tr}(J)$$

Subject To:

$$\begin{bmatrix}
J & B^*Y - D^*V^* \\
YB - VA & V
\end{bmatrix} \geq 0,$$  \hspace{1cm} (30)

$$\begin{bmatrix}
Y & \sum_{j=1}^{m} YN_j + YA - VC \\
\sum_{j=1}^{m} N_j^* Y + A^*Y - C^*V^* & Y \end{bmatrix} \geq 0,$$  \hspace{1cm} (31)

$$Y \geq 0,$$  \hspace{1cm} (32)

where $Y = Y^* \in R^{n \times n}$, $V \in R^{n \times r}$ and $J = J^* \in R^{m \times m}$. The optimal solution is such that:

$$\text{Tr}(J) = \min \|E\|^2_2$$  \hspace{1cm} (33)

and the optimal $H_2$ filtering gain is given by:

$$K = Y^{-1}V.$$  \hspace{1cm} (34)

**Proof:**

Suppose that there exist $Y \geq 0$ and $V$, satisfying (31). Then, from Schur’s complement we have:

$$\begin{bmatrix}
(\sum_{j=1}^{m} YN_j + YA - VC)Y^{-1}(\sum_{j=1}^{m} YN_j + YA - VC) - Y + L^*L & 0 \\
0 & L^*L
\end{bmatrix} \leq 0$$

Equivalently, we have:

$$\begin{bmatrix}
(\sum_{j=1}^{m} N_j^* + A - Y^{-1}VC)Y(\sum_{j=1}^{m} N_j^* + A - Y^{-1}VC) - Y + L^*L & 0 \\
0 & L^*L
\end{bmatrix} \leq 0$$

For $K = Y^{-1}V$ and $Y = \tilde{Q}_\psi$.
Therefore:

\[ A^* \dot{Q} \dot{A} - \dot{Q} + \sum_{j=1}^{m} N_j^* \dot{Q} N_j + L^* L \leq 0, \]

Corollary 3 applies and therefore we have:

\[ \text{Tr}(B^*_u Y B_v) \geq \text{Tr}(B^*_u \dot{Q} B_v). \]

(35)

On the other hand, from (30) using Schur complement we get:

\[ J - (YB - VD)^* Y^{-1} (YB - VD) \geq 0 \]

Therefore:

\[ \text{Tr}(J) \geq \text{Tr}((YB - VD)^* Y^{-1} (YB - VD)) = \text{Tr}(B^*_u Y B_v) \]

From this and (35), we have:

\[ \text{Tr}(J) \geq \text{Tr}(B^*_u \dot{Q} B_v) = \|E\|_2^2. \]

(36)

Since no other constraint is imposed on the \( J \), the minimization of the linear cost ensures that:

\[ \text{Tr}(J) = \min \|E\|_2^2 \]

(37)

This theorem is used for \( H_2 \) optimal filtering of a bilinear hydraulic derive system in the next section.

4. \( H_2 \) OPTIMAL FILTERING OF A BILINEAR HYDRAULIC DERIVE SYSTEM

In general, hydraulic systems are highly nonlinear dynamical systems. The linear models are not sufficiently accurate to describe them and consequently the controllers which are designed based on the linear models of the hydraulic systems quite often do not end up with satisfying results. On the other hand, due to the complexity of the highly nonlinear hydraulic models, methods for analyzing them, filtering and synthesizing their controllers are not well developed and often they are difficult to apply in practice. In between the spectrum of different models to describe them and consequently the controllers which

were developed and often they are difficult to apply in practice.

The \( H_2 \) optimal filter is formulated in the convex optimization framework of linear systems, to the best of our knowledge, it has not been studied for bilinear systems. Due to the importance of this class of nonlinear systems, the problem of \( H_2 \) optimal filtering for discrete-time bilinear systems has been addressed in this paper. The filter design problem has been formulated in the convex optimization framework using linear matrix inequalities. The results have been successfully used for the optimal filtering of a bilinear model of an electro-hydraulic drive.

\begin{equation}
A^* \dot{Q} \dot{A} - \dot{Q} + \sum_{j=1}^{m} N_j^* \dot{Q} N_j + L^* L \leq 0,
\end{equation}

where:

\[ A = \begin{bmatrix} 1 & 0 & 0 & -0.00002 \\ 0.1 & 1 & 0 & -0.00225 \\ 0 & 0.1 & 1 & -0.06600 \\ 0 & 0 & 0.1 & 0.41370 \end{bmatrix}, \quad B = \begin{bmatrix} 0.00014 \\ 0 \\ 0 \\ 0 \end{bmatrix}, \quad C = \begin{bmatrix} 0 & 0 & 0 & 1 \end{bmatrix}, \quad L = \begin{bmatrix} 0 & 0 & 0 \end{bmatrix}, \]

\begin{equation}
N = \begin{bmatrix} 0 & 0 & 0.00003 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}.
\end{equation}

Applying Theorem 1, the solution to the optimization problem is:

\[ Y = \begin{bmatrix} 0.00036 & -0.00432 & 0.05733 & -0.77669 \\ -0.00432 & 0.08411 & -1.40225 & 21.68466 \\ 0.05733 & -1.40225 & 27.68576 & -487.88060 \\ -0.77669 & 21.68466 & -487.88060 & 9585.27364 \end{bmatrix}, \]

\[ V = \begin{bmatrix} -0.58546327196 \\ 19.36260729131 \\ -514.30992621789 \\ 11598.15417677910 \end{bmatrix}, \quad J = 7.55316291347e - 012. \]

The optimal \( H_2 \) filtering constant gain is given by:

\[ K = \begin{bmatrix} 946.6941734529101 \\ 423.913743225211 \\ 65.09278123427475 \\ 3.6408492106137 \end{bmatrix}. \]

The \( H_2 \) estimation error is:

\[ \|E\|_2^2 = 7.55316291347e - 012. \]

5. CONCLUSION

Over the last few decades, several approaches such as \( H_2 \) optimal filtering and \( H_\infty \) optimal filtering have been developed for filtering. While the \( H_2 \) optimal filtering problem has been extensively studied in the past for linear systems, to the best of our knowledge, it has not been studied for bilinear systems. Due to the importance of this class of nonlinear systems, the problem of \( H_2 \) optimal filtering for discrete-time bilinear systems has been addressed in this paper. The filter design problem has been formulated in the convex optimization framework using linear matrix inequalities. The results have been successfully used for the optimal filtering of a bilinear model of an electro-hydraulic drive.

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