Research Article

$H_\infty$ Filter Design for Large-Scale Systems with Missing Measurements

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This paper is concerned with $H_\infty$ filter design problem for large-scale systems with missing measurements. The occurrence of missing measurements is assumed to be a Bernoulli distributed sequence with known probability. The new full-dimensional filter is designed to make the filter error system exponentially mean-square stable and achieve a prescribed $H_\infty$ performance. Sufficient conditions are derived in terms of linear matrix inequality (LMI) for the existence of the filter, and the parameters of filter are obtained by solving the LMI. Finally, the numerical simulation results illustrate the effectiveness of the proposed scheme.

1. Introduction

In many practical applications, due to the limitations imposed by the network, missing measurements often occur due to the network link transmission errors, network congestion, and so forth. Currently, the research of filter and controller design for systems with missing measurements has attracted more attention [1–7]. In [1], the robust control problem with missing measurements was investigated, where the missing measurements were described by a binary switch sequence satisfied conditional probability distribution. The similar model was employed in [2–4], where the filtering problem was investigated in [2, 3], and the distributed state estimation problem was studied in [4]. In [5], the quantized $H_\infty$ control problem is investigated for a class of nonlinear stochastic time-delay network-based systems with probabilistic data missing. In [6], the filtering problem with packet loss was considered using Markov chains to describe probabilistic losses. The problem of robust $H_\infty$ filtering for discrete-time switched systems with missing measurements under asynchronous switching is considered in [7].

Most of the existing research is focused on general linear or nonlinear discrete system. However, many actual systems are large-scale systems which are composed of interconnected subsystems. Although ideas of decentralized control of large-scale systems have attracted much attention in the literature during the past two decades, the research about large-scale systems with missing measurements is seldom. In [8], a decentralized $H_\infty$ controller design for a class of large-scale systems with missing measurements is considered. In [9], a state feedback $H_\infty$ controller is designed for a class of linear discrete-time large-scale system with both measurement data and control data missing simultaneously.

In this paper, $H_\infty$ filter is considered for a class of large-scale systems with missing measurements. We apply Bernoulli distributed sequence to describe the occurrence of missing measurements, and the linear discrete-time large-scale system is modeled as interconnection of $N$ subsystems with missing measurements. Then, we design a new decentralized filter. Sufficient conditions are derived in terms of linear matrix inequality (LMI) which is easy to be solved by using MATLAB LMI Toolbox for the decentralized stabilization of this class of large-scale system.

2. Problem Formulation

Consider the linear discrete-time large-scale system comprising $N$ subsystems $\Sigma_i, i = 1, 2, \ldots, N$; the dynamics of the $i$th subsystem is described by
\[ \Xi_i : \begin{cases} x_i(k+1) = A_i x_i(k) + B_i w_i(k) + \sum_{j=1}^{N} G_{ij} x_j(k) \\ z_i(k) = C_i x_i(k) + D_i w_i(k) \\ y_i(k) = x_i(k) , \end{cases} \]

where \( x_i(k) \in \mathbb{R}^{n_i} \) is the state vector of the \( i \)th subsystem at time \( k \), \( y_i(k) \in \mathbb{R}^{l_i} \) is the measurement output, \( z_i(k) \in \mathbb{R}^{p_i} \) is the controlled output, \( w_i(k) \in \mathbb{R}^{q_i} \) is the disturbance vector belonging to \( i \)th subsystem, and \( A_i, B_i, C_i, D_i \) are known constant matrices with appropriate dimensions, and \( G_{ij} \in \mathbb{R}^{n_i \times n_j} \) is the interconnection matrix of the subsystem of \( j \) and \( i \).

The measurement with missing data can be characterized by

\[ \Xi_i(k) = \alpha_i (k) x_i(k) , \]

where \( \Xi_i(k) \in \mathbb{R}^{n_i} \) is the actual measured state, the stochastic variable \( \alpha_i(k) \in \mathbb{R} \) is a Bernoulli distributed white noise sequence taking the values of 0 and 1 with certain probability

\[ \text{prob} \{ \alpha_i(k) = 1 \} = E \{ \alpha_i(k) \} := \overline{\alpha}_i , \]

\[ \text{prob} \{ \alpha_i(k) = 0 \} = 1 - E \{ \alpha_i(k) \} := 1 - \overline{\alpha}_i , \]

and \( 0 < \overline{\alpha}_i < 1 \) is a known positive constant.

In order to observe the states of the system (1), we consider the following filter of order \( n \) described by

\[ \begin{align*}
\hat{x}_i(k+1) &= A_i \hat{x}_i(k) + \sum_{j=1}^{N} G_{ij} \hat{x}_j(k) + K_i (\Xi_i(k) - \hat{x}_i(k)) , \\
\hat{z}_i(k) &= C_i \hat{x}_i(k), \\
\hat{y}_i(k) &= \hat{x}_i(k),
\end{align*} \]

where \( \hat{x}_i(k) \in \mathbb{R}^{n_i} \) is the state estimate of system (1) and \( K_i \) is the observer gain to be determined later.

Define the state estimation error by

\[ e_i(k) = x_i(k) - \hat{x}_i(k) , \]

and the filter output error is denoted by

\[ \epsilon_i(k) = z_i(k) - \hat{z}_i(k) . \]

Then it follows from (1), (2), (4) that

\[ \begin{align*}
e_i(k+1) &= (A_i + \overline{\alpha}_i K_i) e_i(k) + \sum_{j=1}^{N} G_{ij} e_j(k) \\
&\quad + (\alpha_i(k) - \overline{\alpha}_i) K_i x_i(k) + B_i w_i(k) , \end{align*} \]

\[ e_i(k) = z_i(k) - \hat{z}_i(k) = C_i e_i(k) + D_i w_i(k) . \]

Definition 1 (see [10]). The filter error system (8) is said to be exponentially mean-square asymptotically stable if with \( w(k) = 0 \), there exist constants \( \kappa > 0 \) and \( 0 < \tau < 1 \), such that

\[ E \left\{ \| e(k) \|^2 \right\} < \kappa \tau E \left\{ \| e(0) \|^2 \right\} , \quad \forall e(k) \neq 0 , \]

where \( e(k) = [e_1^T(k) \cdots e_N^T(k)]^T \) and \( w(k) = [w_1^T(k) \cdots w_N^T(k)]^T \).

With this definition, our objective is to design the full-order filter of form (4), such that

1. the filter error system (8) is exponentially mean-square asymptotically stable with \( w(k) = 0 \);
2. under zero-initial condition, the filter error \( e(k) \) satisfies

\[ \sum_{k=0}^{\infty} E \left\{ \| e(k) \|^2 \right\} < \gamma^2 \sum_{k=0}^{\infty} E \left\{ \| w(k) \|^2 \right\} , \]

where \( \gamma \) is a given positive constant.

3. Main Results

For investigating the stability conditions of the filter error system (8), the following lemma is needed.

Lemma 2 (see [10]). Let \( V(\eta(k)) \) be a Lyapunov functional. If there exist constants \( \lambda \geq 0 \), \( \mu > 0 \), \( \nu > 0 \), and \( 0 < \psi < 1 \) such that

\[ \mu \| \eta(k) \|^2 \leq V(\eta(k)) \leq \nu \| \eta(k) \|^2 , \]

\[ E \{ V(\eta(k+1) | \eta(k)) \} - V(\eta(k)) \leq \lambda - \psi V(\eta(k)) , \]

then the sequence \( \eta(k) \) satisfies

\[ E \left\{ \| \eta(k) \|^2 \right\} < \frac{\nu}{\mu} \| \eta(0) \|^2 (1 - \psi)^k + \frac{\lambda}{\mu \psi} . \]

The main results are concluded into the following theorems.

Theorem 3. Given \( 0 < \overline{\alpha}_i < 1 \) and \( w(k) = 0 \), the filter error system (8) is exponentially mean-square asymptotically stable if there exist positive definite matrices \( P_{1i} = P^T_{1i} \), \( P_{2i} = P^T_{2i} \) and gain matrix \( K_i, i = 1, 2, \ldots, N \), satisfying

\[ \begin{bmatrix}
-P_1 & 0 & Q_1^T + \overline{\alpha}_i K & 0 & 0 \\
0 & -P_2 & 0 & Q_1^T & K \\
Q_1 + \overline{\alpha}_i K & 0 & -P_1^{-1} & 0 & 0 \\
0 & Q_1 & 0 & -P_2^{-1} & 0 \\
0 & K & 0 & 0 & -\beta^2 P_1^{-1}
\end{bmatrix} < 0 , \]

where

\[ -\beta^2 = \begin{bmatrix} -\beta & 0 & \cdots & 0 \\
0 & -\beta & \cdots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
0 & 0 & \cdots & -\beta \end{bmatrix} , \]

\( \beta, \beta_i > 0 \).
where

\[
Q_1 = \begin{bmatrix}
A_1 & G_{12} & \cdots & G_{1N} \\
G_{21} & A_2 & \cdots & G_{2N} \\
\vdots & \vdots & \ddots & \vdots \\
G_{N1} & G_{N2} & \cdots & A_N
\end{bmatrix},
\]

\[
P_1 = \text{diag} \{ P_{11}, P_{12}, \ldots, P_{1N} \},
\]

\[
P_2 = \text{diag} \{ P_{21}, P_{22}, \ldots, P_{2N} \},
\]

\[
K = \text{diag} \{ K_1, K_2, \ldots, K_N \}, \quad \beta = \text{diag} \{ \beta_1, \beta_2, \ldots, \beta_N \},
\]

\[
\beta_i = ((1 - \overline{\alpha}_i) \overline{\alpha}_i)^{1/2}, \quad i = 1, 2, \ldots, N,
\]

\[
\overline{\alpha} = \text{diag} \{ \overline{\alpha}_1, \overline{\alpha}_2, \ldots, \overline{\alpha}_N \}.
\]

(14)

Proof. When \( w(k) = 0 \), define the Lyapunov functional

\[
V(k) = \sum_{i=1}^{N} \left( A_i + \overline{\alpha}_i K_i \right) \epsilon_i(k) \left( \sum_{j=1}^{N} G_{ij} \epsilon_j(k) + (\alpha_i(k) - \overline{\alpha}_i) K_i x_i(k) \right)^T P_{1i}
\]

\[
\times \left( A_i + \overline{\alpha}_i K_i \right) \epsilon_i(k) + \sum_{j=1}^{N} G_{ij} \epsilon_j(k) \left( \sum_{j=1}^{N} G_{ij} x_j(k) \right)
\]

\[
+ \sum_{j=1}^{N} G_{ij} \epsilon_j(k) \left( \sum_{j=1}^{N} G_{ij} x_j(k) \right)
\]

\[
\times \left( A_i + \overline{\alpha}_i K_i \right) \epsilon_i(k) + \sum_{j=1}^{N} G_{ij} \epsilon_j(k) \left( \sum_{j=1}^{N} G_{ij} x_j(k) \right)
\]

\[
- \sum_{i=1}^{N} \epsilon_i(k) P_{1i} \epsilon_i(k) - \sum_{i=1}^{N} x_i(k) P_{2i} x_i(k).
\]

(16)

Noting that \( E[\alpha_i(k) - \overline{\alpha}_i] = 0 \), \( E[(\alpha_i(k) - \overline{\alpha}_i)^2] = (1 - \overline{\alpha}_i) \overline{\alpha}_i \leq \beta_i^2 \), we have

\[
E \{ V(k+1) \} - V(k)
\]

\[
= \sum_{i=1}^{N} \left( (A_i + \overline{\alpha}_i K_i) \epsilon_i(k) + \sum_{j=1}^{N} G_{ij} \epsilon_j(k) \right) P_{1i}
\]

\[
\times \left( A_i + \overline{\alpha}_i K_i \right) \epsilon_i(k) + \sum_{j=1}^{N} G_{ij} \epsilon_j(k) \left( \sum_{j=1}^{N} G_{ij} x_j(k) \right)
\]

\[
+ \sum_{i=1}^{N} \beta_i^2 (K_i x_i(k))^T P_{1i} (K_i x_i(k))
\]

\[
+ \sum_{i=1}^{N} \epsilon_i(k) P_{1i} \epsilon_i(k) - \sum_{i=1}^{N} x_i(k) P_{2i} x_i(k)
\]

\[
= \eta^T(k) \theta_1 \eta(k),
\]

where

\[
x(k) = \begin{bmatrix} x_1^T(k) & \cdots & x_N^T(k) \end{bmatrix}^T,
\]

\[
\epsilon(k) = \begin{bmatrix} \epsilon_1^T(k) & \cdots & \epsilon_N^T(k) \end{bmatrix}^T,
\]

\[
\eta(k) = \begin{bmatrix} \eta_1^T(k) & \cdots & \eta_N^T(k) \end{bmatrix}^T.
\]

By Schur complement, inequality (13) implies \( \theta_1 < 0 \). Then we have

\[
E \{ V(k+1) \} - V(k) = \eta^T(k) \theta_1 \eta(k)
\]

\[
\leq -\lambda_{\text{min}}(\theta_1) \eta^T(k) \eta(k)
\]

\[
< -\gamma \eta^T(k) \eta(k),
\]

where \( 0 < \gamma < \min\{\lambda_{\text{min}}(-\theta_1), \sigma\} \), and then from (18), we get

\[
E \{ V(k+1) \} - V(k) < -\gamma \eta^T(k) \eta(k)
\]

\[
< -\frac{\psi}{\sigma} \psi V(\eta(k)) = -\psi V(\eta(k)),
\]

where \( \psi = \gamma/\sigma \in (0, 1) \).

From Definition 1 and Lemma 2, we can conclude that the filter error system (8) is exponentially mean-square asymptotically stable. This completes the proof.

In the sequel, we further provide method for solving matrix inequality (13) that is not a linear matrix inequality (LMI).
Theorem 4. Given $0 < \alpha_i < 1$ if there exist positive definite matrices $M_1 = M_1^T$, $M_2 = M_2^T$ and gain matrices $N_1, N_2$ that satisfy linear matrix inequality
\[
\begin{bmatrix}
  -M_1 & 0 & M_1^T \alpha N_1 & 0 & 0 \\
  0 & -M_2 & 0 & M_2^T \alpha N_2 \\
  Q_1 M_1 + \alpha N_1 & 0 & -M_2 & 0 \\
  0 & Q_1 M_2 & 0 & -M_1 \\
  \beta N_1 & \beta N_2 & 0 & 0 & 0 \\
\end{bmatrix} < 0
\]
then
\[
E\{V(k+1)\} - V(k) + E\left\{e^T(k) e(k)\right\} - \gamma^2 E\left\{w^T(k) w(k)\right\} < 0
\]
(20)
and equation
\[
\eta(\theta) = \eta(\theta) + \nabla \eta(\theta) a(k)
\]
(21)
where $M_1 = P_1^{-1}$, $M_2 = P_2^{-1}$, $N_1 = K P_1^{-1}$, and $N_2 = K P_2^{-1}$, then the error system (8) is exponentially mean-square asymptotically stable.

Proof. Through left- and right-multiplying (13) by $\text{diag}[P_1^{-1}, P_2^{-1}, I, I, \beta I]$, we have
\[
\begin{bmatrix}
  -P_1 & 0 & P_1^{-1} (Q_1 + \alpha K) \beta P_2^{-1} K \\
  0 & -P_2 & 0 \\
  (Q_1 + \alpha K) P_1^{-1} & 0 & -P_2 \beta P_2^{-1} K \\
  0 & (Q_1 P_1^{-1} + \alpha K P_2^{-1}) & 0 \\
  0 & 0 & -P_1 \beta P_2^{-1} K \\
\end{bmatrix} < 0.
\]
(22)
For the definitions of the matrices $M_1, M_2, N_1,$ and $N_2$, the matrix inequality (13) is equivalent to (20) and (21). This completes the proof.

By solving the linear matrix inequality (20) and (21), we have $M_1, M_2, N_1,$ and $N_2$. Moreover, the matrices are given by $P_1 = M_1^{-1}, P_2 = M_2^{-1}$, and $K = N_1 P_1 = N_2 P_2$.

Theorem 5. Given $0 < \alpha_i < 1$ if there exist positive definite matrices $P_{1i} = P_{1i}^T$, $P_{2i} = P_{2i}^T$ and gain matrix $K_i i = 1, 2, \ldots, N$, that satisfy the following linear matrix inequality:
\[
\begin{bmatrix}
  -P_1 & * & * & * & * & * \\
  0 & -P_2 & * & * & * & * \\
  0 & 0 & -\gamma^2 I & * & * & * \\
  Q_1 + \alpha K & 0 & B & -P_1^{-1} & * & * \\
  0 & Q_1 B & 0 & -P_2^{-1} & * & * \\
  C & 0 & D & 0 & 0 & -I \\
\end{bmatrix} < 0,
\]
(23)
where $C = \text{diag}[C_1, C_2, \ldots, C_N]$, $D = \text{diag}[D_1, D_2, \ldots, D_N]$, $B = \text{diag}[B_1, B_2, \ldots, B_N]$, and $Q_1, P_1, P_2, K_i, \alpha_i, \beta_i$, and $\beta$ are the same as (13), then the filter error system (8) is exponentially mean-square asymptotically stable and achieves the prescribed $H_{\infty}$ performance.

Proof. When $w(k) = 0$, (23) is equivalent to (13), so the filter error system is exponentially mean-square asymptotically stable.

When $w(k) \neq 0$, define the Lyapunov functional as
\[
V(k) = \sum_{i=1}^{N} e_i^T(k) P_i e_i(k) + \sum_{i=1}^{N} x_{ki}^T(k) P_{2i} x_{ki}(k),
\]
(24)
Since the system is exponentially mean-square asymptotically stable, it is straightforward to see that
\[
\sum_{k=0}^{\infty} E \left\{ \| e(k) \|^2 \right\} < \gamma^2 \sum_{k=0}^{\infty} E \left\{ \| w(k) \|^2 \right\},
\]
under the zero-initial condition. This completes the proof.

In the sequel, we further present how to convert the matrix inequality (23) into an LMI with matrix equality constraint.

**Theorem 6.** Given \(0 < \alpha < 1\) if there exist positive definite matrices \(M_1^T = M_1, M_2^T = M_2\) and gain matrices \(N_1, N_2\) that satisfy the following linear matrix inequality
\[
\begin{bmatrix}
-M_1 & * & * & * & * & * & * \\
0 & -M_2 & * & * & * & * & * \\
0 & 0 & -\gamma^2 I & * & * & * & * \\
Q_1 M_1 + \alpha N_1 & 0 & B & -M_1 & * & * & * \\
0 & Q_1 M_2 & B & 0 & -M_2 & * & * \\
0 & 0 & \beta N_2 & 0 & 0 & 0 & -M_1 & * \\
C M_1 & 0 & D & 0 & 0 & 0 & 0 & -I
\end{bmatrix} < 0,
\]
then the filter error system (8) is exponentially mean-square asymptotically stable and achieves the prescribed \(H_{\infty}\) performance.

**Proof.** Through left- and right-multiplying (23) by \(\text{diag}(P_1^{-1}, P_2^{-1}, I, I, I, \beta I, I) > 0\), we have
\[
\begin{bmatrix}
-P_1^{-1} & * & * & * & * & * & * \\
0 & -P_2^{-1} & * & * & * & * & * \\
0 & 0 & -\gamma^2 I & * & * & * & * \\
(Q_1 + \alpha K) P_1^{-1} & 0 & B & -P_1^{-1} & * & * & * \\
0 & Q_1 P_2^{-1} & B & 0 & -P_2^{-1} & * & * \\
0 & 0 & \beta K P_2^{-1} & 0 & 0 & 0 & -P_1^{-1} & * \\
C P_1^{-1} & 0 & D & 0 & 0 & 0 & 0 & -I
\end{bmatrix} < 0.
\]
(29)

Similar to the proof of Theorem 4, we define \(M_1 = P_1^{-1}, M_2 = P_2^{-1}, N_1 = KP_1^{-1}, \) and \(N_2 = KP_2^{-1}\). Then the matrix inequality (29) is equivalent to (23). From Theorem 5, we can conclude that the filter error system (8) is exponentially mean-square asymptotically stable and achieves the prescribed \(H_{\infty}\) performance. The proof is completed.

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**4. Numerical Simulations**

Consider a linear discrete-time large-scale system which consists of two interconnected subsystems:
\[
x_1(k+1) = \begin{bmatrix} -1 & 3 \\ 0 & -0.1 \end{bmatrix} x_1(k) + \begin{bmatrix} 0.2 & 0.3 \\ 0.1 & 0.2 \end{bmatrix} x_2(k) \\
+ \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix} w_1(k) \\
= A_1 x_1(k) + B_1 x_2(k) + E_1 w_1(k),
\]
\[
z_1 = \begin{bmatrix} 1 & 0 \\ -1 & 0.8 \end{bmatrix} x_1(k) + \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} w_1(k)
\]
\[
= C_1 x_1(k) + D_1(w_1(k),
\]
\[
y_1(k) = x_1(k),
\]
(30)
\[
x_2(k+1) = \begin{bmatrix} -1 & 1 \\ 0 & -0.2 \end{bmatrix} x_2(k) + \begin{bmatrix} 0.3 & 0.1 \\ 0.2 & 0.2 \end{bmatrix} x_1(k) \\
+ \begin{bmatrix} 0 & 0 \\ 1 & 0 \end{bmatrix} w_2(k)
\]
\[
= A_2 x_2(k) + B_2 x_1(k) + E_2 w_2(k),
\]
\[
z_2 = \begin{bmatrix} 1 & 0 \\ 1 & -0.8 \end{bmatrix} x_2(k) + \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} w_2(k)
\]
\[
= C_2 x_2(k) + D_2(w_2(k),
\]
\[
y_2(k) = x_2(k).
\]

Choose the disturbance input \(w_1(k) = w_2(k) = 0.01 \begin{bmatrix} \sin(100k) \\ \sin(100k) \end{bmatrix}\). The initial state values of original system and its observer are \(x_1(0) = [\frac{2}{3}, \frac{3}{2}]\), \(x_2(0) = [\frac{3}{4}, \frac{1}{2}]\), and \(\hat{x}_1(0) = [\frac{1}{3}, \frac{2}{5}]\), respectively. Suppose that stochastic sequence obeys Bernoulli distribution with probability \(E[\alpha_1(k) | \alpha_1(k) = 1] = E[\alpha_2(k) | \alpha_2(k) = 1] = 0.996\), given \(\gamma = 1\). For simplicity, let \(M_1 = P_1^{-1} = P_2^{-1}\) and \(N_1 = KP_1^{-1} = KP_2^{-1}\). We can obtain the following parameters in Theorem 6 by using the MATLAB YALMIP Toolbox:

\[
M_1 = \begin{bmatrix} 1.3549 & 0.4014 \\ 0.4014 & 0.3819 \end{bmatrix},
M_2 = \begin{bmatrix} 1.1058 & 0.7881 \\ 0.7881 & 1.6449 \end{bmatrix},
\]
\[
N_1 = \begin{bmatrix} 0.1755 & -0.3232 \\ -0.3232 & 0.0041 \end{bmatrix},
N_2 = \begin{bmatrix} 0.2464 & -0.3847 \\ -0.3847 & 0.3580 \end{bmatrix}.
\]
(31)
The Lyapunov function solution matrices and observer parameters are given by

\[
P_{11} = P_{21} = M_1^{-1} = \begin{bmatrix} 1.0718 & -1.1264 \\ -1.1264 & 3.8021 \end{bmatrix}, \\
P_{12} = P_{22} = M_2^{-1} = \begin{bmatrix} 1.3732 & -0.6579 \\ -0.6579 & 0.9231 \end{bmatrix}, \\
K_1 = N_1 P_1 = \begin{bmatrix} 0.5521 & -1.4264 \\ -0.3510 & 0.3789 \end{bmatrix}, \\
K_2 = N_2 P_2 = \begin{bmatrix} 0.5919 & -0.5172 \\ -0.7637 & 0.5835 \end{bmatrix}. \tag{32}
\]

The simulation results are shown in Figures 1, 2, 3, and 4.

It can be verified that \(\sum_{k=0}^{\infty} E\|e(k)\|^2 < \gamma^2 \sum_{k=0}^{\infty} \|w(k)\|^2\) and the filter error system satisfies the prescribed \(H_\infty\) performance.

5. Conclusion

In this paper, the \(H_\infty\) filter for a class of linear discrete-time large-scale system has been designed, where the measurements are probably missing. The missing probability is assumed to obey Bernoulli distribution. By employing the Lyapunov stability theory combined with stochastic analysis method, a filter is designed to reconstruct the states of original system such that the filter error system is exponentially stable in the sense of mean square and achieves the prescribed \(H_\infty\) performance.

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