Robust Non-fragile Filtering for Networked Systems with Distributed Variable Delays

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Abstract

This paper is concerned with the robust non-fragile filtering for a class of networked systems with distributed variable delays. We model such a complex delay system with an augmented switched system. For the filtering implementation uncertainty, a stochastic variable is employed to indicate random occurrence of the filter gain change, and a norm bound to measure the change size. The suitably weighted measurements are proposed for filter performance improvement, instead of direct use of the measurements themselves which may have significant delays and degrade the performance. With some improved stability and l_2 gain analysis for the switched systems, a new sufficient condition is obtained such that the filtering error system is exponentially stable in the mean square sense and achieves a prescribed H_∞ performance level. A numerical example is given to show the effectiveness of the proposed design.

Index Terms

Networked systems, distributed delays, variable delays, non-fragile filtering, H_∞ filtering, switched systems.

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I. Introduction

In the last decades, analysis and design of networked control systems (NCSs) have received much attention due to their advantages such as low cost and easy installation. However, insertion of the communication network into the control loop brings many other problems, e.g., network-induced delay [1], [2], packet dropout [3], [4], quantization error [5] and so on. They may degrade the system performance or even lead to the instability of control systems. Till now, many methods have been proposed to design the NCSs with these networked issues. For example, the authors in [2] used a Markov model to model the NCSs with random communication delay, and the controller design method was derived based on the Markov system theory. In [3], a binary variable was introduced to model the networked transmission process, where the measurement may be lost. On the basis of the Lyapunov stability theory and the linear matrix inequality technique, the output feedback controller design algorithm was presented by the authors in [3]. Recent developments on the NCSs can be found in the survey papers [6] and [7].

Except for the stabilization problem, considerable efforts have been devoted onto the state estimation/filtering for networked systems, see [8-13], and most of which focused on how to design the filter based on the delayed measurement, e.g., [8]-[11]. It should be pointed out that these works only considered the single channel case, i.e., multiple measurements are incorporated into one packet and then transmitted to the remote filter through the communication channel. However, in many systems, sensors are often deployed in a large geographical region and thus cant be grouped into one packet. In this scenario, multiple distributed delays are inevitable. It is noted that this issue has not received enough attention compared with the single delay case. Recently, the fault detection for networked systems with multiple distributed delays has been considered in [14], but they simply transformed the fault detection system into a time-delay system. The fault detector gains were finally derived based on the time-delay system theory. Such a detector design may be conservative in some extent as the properties of different channels were ignored. In addition, the delayed measurement was directly used for the filter design in [8]-[11] and [14], which may also be conservative. We will address these issues in this paper.

On the other hand, uncertainties may occur in the implementation of the designed filter even though it is well designed. Such uncertainties exist due to unexpected errors during the filter implementation, e.g., due to round off errors in numerical computation, programming errors and so on. Thus, the filter should be designed such that the filter is insensitive to some amount of errors with respect to its gain, i.e., the designed filter is resilient or non-fragile. This issue has received considerable attention from the control community, and many results have been reported in the last decades [15-19]. In [16], the authors studied the non-fragile filtering problem for a class of fuzzy systems, and the additive filter gain perturbation case was addressed. They showed that the optimal filter gain can be determined by solving a set of linear matrix inequalities. Note that the current methods work on the assumption of deterministic and persistent uncertainty, see [15-19] for more details. In reality, however, during the operation of estimation task, the occurrence of uncertainty in the filter gain may be intermittently as the filter can be implemented accurately in most of the time. We formulate the intermittent filter gain phenomenon into a stochastic framework. Then, what is the relation between the occurrence probability of uncertainty and the filtering performance? To the best of the authors' knowledge, the non-fragile filtering for a class of networked systems with *distributed variable delays* and *random filter gain changes* has not been investigated yet, this motivates the present study.

In this paper, the robust non-fragile filtering problem is addressed for a class of networked systems with distributed variable delays and random filter gain changes. Due to the existence of the uncertainties in the filtering systems, we resort to the H_∞ filtering technique, which is more robust to uncertainties than that of the Kalman filtering. With the switched system approach and the stochastic analysis, a new sufficient condition is obtained such that the filtering error system is exponentially stable in the mean-square sense and achieves a prescribed H_∞ performance level. Filter gain design is also provided. Finally, a numerical example is given to show the effectiveness of the proposed design.

The rest of this paper is organized as follows. Section II formulates the problem under consideration. The proposed solution is presented in Section III. A case study of the satellite yaw angles control system is presented in Section IV. We conclude our work in Section V.

Notation: The notation in this paper is fairly standard. We use W^T, and $\psi(W)$ to denote, respectively, the transpose, and the eigenvalues of any square matrix W. We use $W > 0$ to denote a positive-definite matrix W with $\sigma_{\min}(W)$ and $\sigma_{\max}(W)$ being the minimum and maximum eigenvalues of W and $I_{n\times n}$ to denote the $n \times n$ identity matrix. Let R^n denote the n dimensional Euclidean space. $\mathrm{R}^{m\times n}$ is the set of all $m\times n$ real matrices. The notation $l_2[0, \infty)$ refers to the space of square summable infinite vector sequences with the norm $||\bullet||_2$. The symbol "*" will be used in some matrix expressions to represent the symmetric terms. Moreover, $\mathbb{E}\{\bullet\}$ stands for the mathematical expectation.

II. System description

Consider the following discrete-time system:

$$x(k+1) = Ax(k) + Bw(k) \tag{1}$$

where $x(k) \in \mathrm{R}^{n_x}$ is the state, $w(k) \in \mathrm{R}^{n_w}$ is the unknown disturbance signal belonging to $l_2[0, +\infty)$, and A and B are the constant matrices with appropriate dimensions. Suppose that the system has m distributed sensor stations deployed in a large region. Each station yields its measurement signal described by

$$y_p(k) = C_p x(k) + D_p w(k), p = 1, 2, \cdots, m \tag{2}$$

where, $y_p \in \mathrm{R}^{n_p}$. When such a measurement is transmitted with a time stamp to the remote filter via a communication channel, there might be a communication delay. Further, this delay is not fixed but varies from time to time. In this paper, we consider this variable delay case and assume that this delay is upper-bounded by N_p, where $N_p \geq 0$ is an integer and may vary over channels. Then, the most recent measurement which is available at the filter side must be a member of the set, $\left\{y_p(k), y_p(k-1), \cdots, y_p(k-N_p)\right\}$ and it will be used by the filter to update its state estimation.

In the literature, the measurement is directly taken as the filter input, see [8]-[11] and [14] for more details. However, this may not be a good choice as the information is already delayed and may degrade the system performance. In the paper, we propose a simple but effective compensation scheme, i.e., using the weighted measurement signal as the filter input. The filter input $\bar{y}_p(k)$ is one member of $\left\{r_{0p} y_p(k), r_{1p} y_p(k-1), \cdots, r_{N_p p} y_p(k-N_p)\right\}$, where $0 < r_{sp} \leq 1, s = 0, 1, \cdots, N_p$ are called as "forgetting factors", and $r_{0p} = 1$. Let $N = \max\limits_{p=1,2,\cdots,m} \{N_p\}$, and define

$$X(k) = \begin{bmatrix} x^T(k) & x^T(k-1) & \cdots & x^T(k-N) \end{bmatrix}^T, \ W(k) = \begin{bmatrix} w^T(k) & w^T(k-1) & \cdots & w^T(k-N) \end{bmatrix}^T,$$
$$E_{sp} = \begin{bmatrix} 0 & \cdots & 0 & r_{sp} I_{n_x} & 0 & \cdots & 0 \end{bmatrix}, \ H_{sp} = \begin{bmatrix} 0 & \cdots & 0 & r_{sp} I_{n_w} & 0 & \cdots & 0 \end{bmatrix},$$

in which all elements are zeros except for the $(s+1)$-th block is $r_{sp} I_{n_x}$ and $r_{sp} I_{n_w}$, respectively. It follows that

$$\bar{y}_p(k) = C_p E_{sp} X(k) + D_p H_{sp} W(k) \tag{3}$$

To reflect the change of delay, let

$$\rho_i(k) \in \{1, 2, \cdots, N_i + 1\}, i = 1, 2, \cdots, m, \ \ \rho(k) = [\rho_1(k), \rho_2(k), \cdots, \rho_m(k)],$$
$$\bar{E}_{\rho(k)} = [\ E^T_{1,\rho_1(k)} \ \ E^T_{2,\rho_2(k)} \ \ \cdots \ \ E^T_{m,\rho_m(k)} \ ]^T, \ \bar{H}_{\rho(k)} = [\ H^T_{1,\rho_1(k)} \ \ H^T_{2,\rho_2(k)} \ \ \cdots \ \ H^T_{m,\rho_m(k)} \ ]^T.$$

The input vector to the filter can be expressed as

$$\bar{y}(k) = \bar{C} \bar{E}_{\rho(k)} X(k) + \bar{D} \bar{H}_{\rho(k)} W(k) \tag{4}$$

where $\bar{C} = \mathrm{diag}\{C_1, C_2, \cdots, C_n\}$, and $\bar{D} = \mathrm{diag}\{D_1, D_2, \cdots, D_n\}$. Note that the total number of possible sequences of $\rho(k)$ is $\bar{N} = (N_1 + 1) \times (N_2 + 1) \times \cdots \times (N_m + 1)$. We can view $\rho(k)$ as the signal which takes one sequence and specify one particular case of $(\bar{E}_{\rho(k)}, \bar{H}_{\rho(k)})$ at each time instant k. Therefore, system

(4) becomes a switched system with $\rho(k)$ as the switching signal. Alternatively, let $\Gamma = \{1, 2, \cdots, \bar{N}\}$, we can assign each $\rho(k)$ with a $i \in \Gamma$ and use $i \in \Gamma$ as the switching signal.

Remark 1. There is no compensation for the delayed information in [8]-[11] and [14], which corresponds to the special selection of our compensation scheme with $r_{sp} = 1$ for all s and p. However, our scheme in general has this set of scales not equal to one. We will show in the numerical example that such a compensation scheme achieves a much better filtering performance.

Remark 2. Unlike [14] where the communication delays are simplified as a single common time delay, we model the delays as distributed and variable ones. Such a new modeling reflects communication channels more realistically, and can lead to the mode-dependent filter instead of the mode-independent filter designed in [14].

In this paper, we aim to estimate the following signal:

$$z(k) = Lx(k) \tag{5}$$

where $z(k) \in \mathrm{R}^{n_z}$ and L is a constant matrix with appropriate dimension. Taking uncertainty in the filter implementation into account, we propose the following filter to estimate $z(k)$:

$$\begin{cases} x_f(k+1) = [A_{f\rho(k)} + \alpha_1(k)\Delta A_{f\rho(k)}]x_f(k) + [B_{f\rho(k)} + \alpha_1(k)\Delta B_{f\rho(k)}]\bar{y}(k) \\ z_f(k) = [C_{f\rho(k)} + \alpha_1(k)\Delta C_{f\rho(k)}]x_f(k) \end{cases} \tag{6}$$

where $x_f(k) \in \mathrm{R}^{n_x}$ is the filter state and $z_f(k) \in \mathrm{R}^{n_z}$ is the estimate of $z(k)$, $A_{f\rho(k)}, B_{f\rho(k)}$, and $C_{f\rho(k)}$ are the filter parameters to be designed. A binary valuable $\alpha_1(k) \in \{0, 1\}$ is introduced to describe the random gain change phenomenon, with $\alpha_1(k) = 1$ when the filter gains change, and $\alpha_1(k) = 0$ otherwise. In this paper, we do not know the exact occurrence sequence of uncertainties at each time instant, but the probability $\mathbb{E}\{\alpha_1(k) = 1\} = \bar{\alpha}_1$ is assumed to be known. The uncertain perturbation matrices are defined as follows:

Type I- additive case [16]:

$\Delta A_{f\rho(k)} = M_1\Delta_1(k)N_1$, $\Delta B_{f\rho(k)} = M_2\Delta_2(k)N_2$,

$\Delta C_{f\rho(k)} = M_3\Delta_3(k)N_3$;

Type II- multiplicative case [17]:

$\Delta A_{f\rho(k)} = A_{f\rho(k)}M_1\Delta_1(k)N_1$, $\Delta B_{f\rho(k)} = B_{f\rho(k)}M_2\Delta_2(k)N_2$,

$\Delta C_{f\rho(k)} = C_{f\rho(k)}M_3\Delta_3(k)N_3$.

The uncertain terms $\Delta_1(k), \Delta_2(k)$ and $\Delta_3(k)$ are assumed to be $\Delta_t^T(k)\Delta_t(k) \leq \beta_t I, (t = 1, 2, 3)$, where the scalars β_t are the amplitude of uncertainties.

In order to derive the filtering error system, we rewrite system of (1) and (5) as

$$\begin{cases} X(k+1) = \bar{A}X(k) + \bar{B}W(k) \\ z(k) = \bar{L}X(k) \end{cases} \tag{7}$$

where

$$\bar{A} = \begin{bmatrix} A & 0 \\ I_{nN} & 0 \end{bmatrix}, \bar{B} = \begin{bmatrix} B & 0 \\ 0 & 0 \end{bmatrix}, \ \bar{L} = \begin{bmatrix} L & 0 \end{bmatrix}.$$

Let $\eta(k) = \begin{bmatrix} X^T(k) & x_f^T(k) \end{bmatrix}^T$ and $e(k) = z_f(k) - z(k)$. Then for each $i \in \Gamma$, we have the following filtering error system:

$$\begin{cases} \eta(k+1) = \tilde{A}_i\eta(k) + \tilde{B}_iW(k) + \tilde{\alpha}_1(k)\left[\tilde{D}_{1i}\eta(k) + \tilde{D}_{2i}W(k)\right] \\ e(k) = \tilde{C}_i\eta(k) + \tilde{\alpha}_1(k)\tilde{N}_{3i}\eta(k) \end{cases} \tag{8}$$

where

$$\tilde{A}_i = \bar{A}_i + \bar{\alpha}_1\bar{M}_i\bar{\Delta}_1(k)\bar{N}_{1i}, \ \tilde{B}_i = \bar{B}_i + \bar{\alpha}_1\bar{M}_i\bar{\Delta}_1(k)\bar{N}_{2i},$$
$$\tilde{C}_i = \bar{C}_i + \bar{\alpha}_1\tilde{M}_{3i}\Delta_3(k)\bar{N}_3, \ \tilde{N}_{3i} = \tilde{M}_{3i}\Delta_3(k)\bar{N}_3,$$
$$\tilde{D}_{1i} = \bar{M}_i\bar{\Delta}_1(k)\bar{N}_{1i}, \ \tilde{D}_{2i} = \bar{M}_i\bar{\Delta}_1(k)\bar{N}_{2i}, \ \tilde{\alpha}_1(k) = \alpha_1(k) - \bar{\alpha}_1,$$

with

$$\bar{A}_i = \begin{bmatrix} \bar{A} & 0 \\ B_{fi}\bar{C}\bar{E}_i & A_{fi} \end{bmatrix}, \bar{B}_i = \begin{bmatrix} \bar{B} \\ B_{fi}\bar{D}\bar{H}_i \end{bmatrix}, \bar{C}_i = \begin{bmatrix} -\bar{L} & C_{fi} \end{bmatrix},$$
$$\bar{M}_i = \begin{bmatrix} 0 & 0 \\ \tilde{M}_{2i} & \tilde{M}_{1i} \end{bmatrix}, \bar{\Delta}_1(k) = \begin{bmatrix} \Delta_2(k) & 0 \\ 0 & \Delta_1(k) \end{bmatrix},$$
$$\bar{N}_{1i} = \begin{bmatrix} N_2\bar{C}\bar{E}_i & 0 \\ 0 & N_1 \end{bmatrix}, \ \bar{N}_{2i} = \begin{bmatrix} N_2\bar{D}\bar{H}_i \\ 0 \end{bmatrix}, \bar{N}_3 = \begin{bmatrix} 0 & N_3 \end{bmatrix},$$

and

$$\tilde{M}_{1i} = \begin{cases} M_1, & \text{TypeI} \\ A_{fi}M_1, & \text{TypeII} \end{cases}, \tilde{M}_{2i} = \begin{cases} M_2, & \text{TypeI} \\ B_{fi}M_2, & \text{TypeII} \end{cases}, \tilde{M}_{3i} = \begin{cases} M_3, & \text{TypeI} \\ C_{fi}M_3, & \text{TypeII} \end{cases}.$$

We need the following definitions and lemma in our latter development.

Definition 1 [20]. For any $k > k_0$, and any switching signal $\rho(\tau)$, $k_0 \le \tau \le k$, let N_σ denote the number of switching of $\rho(\tau)$ over (k_0, k). If $N_\sigma \le N_0 + (k - k_0)/T_a$ holds for $T_a > 0$ and $N_0 \ge 0$, then T_a is called the average dwell time and N_0 the chatter bound.

Remark 3. In recent years, the switched system approach has been widely utilized in the controller design of the networked control systems with delayed measurement, see [21, 22] and the references therein. In these results, the exponential stability of the closed loop system is guaranteed by using the average dwell time method. In this paper, the average dwell time method will also be used to obtain the stability and l_2 gain performance of the filtering error system. Moreover, as in literature [21]-[26], we choose $N_0 = 0$.

Definition 2. System (8) is called robustly exponentially stable in the mean-square sense, if there exist some scalars $\pi > 0$ and $0 < \chi < 1$, such that the solution $\eta(k)$ of system (8) satisfies $\mathbb{E}\{\|\eta(k)\|\} < \pi\chi^{(k-k_0)}\|\eta(k_0)\|$, $\forall k \geq k_0$.

Definition 3. For given scalars $\gamma > 0$, system (8) is said to be robustly exponentially stable in the mean-square sense and achieves a prescribed H_∞ performance γ, if it is exponentially stable and under zero initial condition, $\sum_{s=0}^{+\infty} \mathbb{E}\{e^T(s)e(s)\} \leq \sum_{s=0}^{+\infty} \gamma^2 w^T(s)w(s)$ holds for all nonzero $w(k) \in l_2[0,\infty)$.

Lemma 1[5]. For given matrices K_1, K_2 and K_3 with appropriate dimensions, and K_1satisfying $\mathrm{K}_1 = \mathrm{K}_1^T$, then

$$\mathrm{K}_1 + \mathrm{K}_2\Delta(k)\mathrm{K}_3^T + \mathrm{K}_3\Delta^T(k)\mathrm{K}_2^T < 0 \tag{9}$$

holds for all $\Delta^{\mathrm{T}}(k)\Delta(k) < I$ if and only if there exists a scalar $\varepsilon > 0$ such that

$$\mathrm{K}_1 + \varepsilon\mathrm{K}_2\mathrm{K}_2^T + \varepsilon^{-1}\mathrm{K}_3\mathrm{K}_3^T < 0 \tag{10}$$

We are now in the position to state our filtering problem.

Filtering Problem: Design a filter in form of (6) such that the filtering error system (8) is robustly exponentially stable in the mean-square sense and achieves a prescribed H_∞ performance level in the presence of distributed variable delays and random filter gains changes.

III. The proposed solution

A sufficient condition is firstly presented for the solvability of our filtering problem in the following theorem.

Theorem 1. For given scalars $\tau > 0, \mu > 1, 0 < \lambda_i < 1, \beta_t > 0$, and $0 < \lambda < 1$, if there exist positive-definite matrices P_i and positive scale ε such that the following inequality

$$\begin{bmatrix} \Omega_1 & \Omega_2 & 0 & \Omega_3 & 0 & \Omega_4 & 0 \\ * & -P_i^{-1} & 0 & 0 & 0 & 0 & \Omega_5 \\ * & * & -P_i^{-1} & 0 & 0 & 0 & \Omega_6 \\ * & * & * & -I & 0 & 0 & \Omega_7 \\ * & * & * & * & -I & 0 & \Omega_8 \\ * & * & * & * & * & -\varepsilon I & 0 \\ * & * & * & * & * & * & -\varepsilon I \end{bmatrix} < 0 \tag{11}$$

$$P_i \leq \mu P_j,\ i, j \in \Gamma, i \neq j \tag{12}$$

$$T_a > T_a^* = -\frac{\ln \mu}{\ln \lambda} \tag{13}$$

hold for all $i \in \Gamma$, then the filtering error system (8) is robustly exponentially stable in the mean-square sense and achieves a prescribed H_∞ performance level $\gamma = \tau\sqrt{\frac{(N+1)(1-\lambda_a)}{1-\lambda_b/\lambda}}$, where, $\lambda_a = \min_{i\in\Gamma}\{\lambda_i\}$, $\lambda_b = \max_{i\in\Gamma}\{\lambda_i\}$, $\lambda > \lambda_b$, and

$$\Omega_1 = \begin{bmatrix} -\lambda_i P_i & 0 \\ 0 & -\tau^2 I \end{bmatrix}, \Omega_2 = \begin{bmatrix} \bar{A}_i^T \\ \bar{B}_i^T \end{bmatrix}, \Omega_3 = \begin{bmatrix} \bar{C}_i^T \\ 0 \end{bmatrix}, \Omega_4 = \begin{bmatrix} \varepsilon \bar{N}_{1i}^T \bar{\Lambda}_1 & \varepsilon \bar{N}_{3i}^T \Lambda_3 \\ \varepsilon \bar{N}_{2i}^T \bar{\Lambda}_1 & 0 \end{bmatrix},$$

$$\Omega_5 = \begin{bmatrix} \bar{\alpha}_1 \bar{M}_i & 0 \end{bmatrix}, \Omega_6 = \begin{bmatrix} \theta_1 \bar{M}_i & 0 \end{bmatrix}, \Omega_7 = \begin{bmatrix} 0 & \bar{\alpha}_1 \tilde{M}_{3i} \end{bmatrix}, \Omega_8 = \begin{bmatrix} 0 & \theta_1 \tilde{M}_{3i} \end{bmatrix},$$

$$\bar{\Lambda}_1 = \begin{bmatrix} \beta_2 I & 0 \\ 0 & \beta_1 I \end{bmatrix}, \bar{\Lambda}_3 = \beta_3 I, \theta_1 = \sqrt{\bar{\alpha}_1(1-\bar{\alpha}_1)}.$$

Proof. see the Appendix.

Remark 4. Based on the time-delay system approach, the relation between the performance of fault detection systems and the time delay has been established in [14]. However, this relation is not quantitative as they only related the performance and the time delay into one matrix inequality. In our theorem 1, we see the H_∞ performance level γ is a monotonic increasing function of the maximal time delay N.

Remark 5. For stability and l_2 gain analysis of the switched systems with average dwell time, one usually introduces a common λ to derive the main results, see, e.g., [21]-[26]. However, this may be conservative in some extent as a common λ needs to satisfy the matrix inequality (10) for all $i \in \Gamma$. In theorem 1, we introduce a set of different λ_i, which may help reduce the conservatism in those results.

Remark 6. Due to the fact that the delay pattern may be unknown, and the extreme case may be that the delay pattern is different from one time instant to another. In this scenario, system (8) becomes a switched system with arbitrary switching. Then, we need to find adequate λ and μ such that $T_a^* \leq 1$. By doing this, Theorem 1 is applicable to any delay pattern case.

Theorem 1 does not give the filter gains directly. We present the filter gain design in the following theorem.

Theorem 2. For given scalars $\tau > 0, \mu > 1, 0 < \lambda_i < 1, \beta_t > 0$, and $0 < \lambda < 1$, if there exist positive-definite matrices P_i and positive scale ε and any matrices G_i of appropriate dimensions such that the following inequality

$$\begin{bmatrix} \Omega_1 & \bar{\Omega}_2 & 0 & \bar{\Omega}_3 & 0 & \bar{\Omega}_4 & 0 \\ * & \bar{P}_i & 0 & 0 & 0 & 0 & \bar{\Omega}_5 \\ * & * & \bar{P}_i & 0 & 0 & 0 & \bar{\Omega}_6 \\ * & * & * & -I & 0 & 0 & \bar{\Omega}_7 \\ * & * & * & * & -I & 0 & \bar{\Omega}_8 \\ * & * & * & * & * & -\varepsilon I & 0 \\ * & * & * & * & * & * & -\varepsilon I \end{bmatrix} < 0 \tag{14}$$

and (12), (13) hold for all $i \in \Gamma$, then our filtering problem is solvable, and the filter gains are determined by $A_{fi} = G_{3i}^{-T} A_{Fi}$, $B_{fi} = G_{3i}^{-T} B_{Fi}$ and $C_{fi} = C_{Fi}$, where

$$\bar{\Omega}_2 = \begin{bmatrix} \bar{\Omega}_{21} \\ \bar{\Omega}_{22} \end{bmatrix}, \bar{\Omega}_3 = \begin{bmatrix} \bar{\Omega}_{31} \\ 0 \end{bmatrix}, \bar{\Omega}_4 = \begin{bmatrix} \bar{\Omega}_{41} \\ \bar{\Omega}_{42} \end{bmatrix},$$
$$\bar{\Omega}_5 = \begin{bmatrix} \bar{\Omega}_{51} & 0 \end{bmatrix}, \bar{\Omega}_6 = \begin{bmatrix} \bar{\Omega}_{61} & 0 \end{bmatrix}, \bar{\Omega}_7 = \begin{bmatrix} 0 & \bar{\Omega}_{71} \end{bmatrix},$$
$$\bar{\Omega}_8 = \begin{bmatrix} 0 & \bar{\Omega}_{81} \end{bmatrix}, \bar{P}_i = P_i - G_i - G_i^T,$$

with

$$\bar{\Omega}_{21} = \begin{bmatrix} \bar{A}^T G_{1i} + \bar{E}_i \bar{C} B_{Fi}^T F_i & \bar{A}^T G_{2i} + \bar{E}_i \bar{C} B_{Fi}^T \\ A_{Fi}^T F_i & A_{Fi}^T \end{bmatrix},$$
$$\bar{\Omega}_{22} = \begin{bmatrix} \bar{B}^T G_{1i} + \bar{H}_i \bar{D} B_{Fi}^T F_i & \bar{B}^T G_{2i} + \bar{H}_i \bar{D} B_{Fi}^T \end{bmatrix},$$
$$\bar{\Omega}_{31} = \begin{bmatrix} -\bar{L} & C_{Fi} \end{bmatrix}^T, \bar{\Omega}_{51} = \begin{bmatrix} \alpha_1 F_i \hat{M}_{2i} & \alpha_1 F_i \hat{M}_{1i} \\ \alpha_1 \hat{M}_{2i} & \alpha_1 \hat{M}_{1i} \end{bmatrix},$$
$$\bar{\Omega}_{61} = \begin{bmatrix} \theta_1 F_i \hat{M}_{2i} & \theta_1 F_i \hat{M}_{1i} \\ \theta_1 \hat{M}_{2i} & \theta_1 \hat{M}_{1i} \end{bmatrix}, \bar{\Omega}_{71} = \bar{\alpha}_1 \hat{M}_{3i}, \bar{\Omega}_{81} = \theta_1 \hat{M}_{3i},$$
$$P_i = \begin{bmatrix} P_{1i} & P_{2i} \\ * & P_{3i} \end{bmatrix}, G_i = \begin{bmatrix} G_{1i} & G_{2i} \\ G_{3i} F_i & G_{3i} \end{bmatrix},$$
$$\hat{M}_{1i} = \begin{cases} G_{3i}^T M_1, & \text{TypeI} \\ A_{Fi} M_1, & \text{TypeII} \end{cases}, \hat{M}_{2i} = \begin{cases} G_{3i}^T M_2, & \text{TypeI} \\ B_{Fi} M_2, & \text{TypeII} \end{cases},$$
$$\hat{M}_{3i} = \begin{cases} M_3, & \text{TypeI} \\ C_{Fi} M_3, & \text{TypeII} \end{cases},$$

F_i is the last n_x elements of $\bar{E}_i$.

***Proof**:* By pre and post multiplying (14) with $\text{diag}\{I, G_i^{-T}, G_i^{-T}, I, I, I, I\}$ and its transpose respectively, then using the inequality $-G_i^T P_i^{-1} G_i \leq P_i - G_i - G_i^T$, it is easy to see that (10) holds under (14). This completes the proof.

Remark 7. In order to obtain the minimum H_∞ performance γ^*, one can solve the following optimization problem:

$$\begin{aligned} &\min \quad \nu \\ &\text{subjectto (12), (13) and (14) with } \nu{=}\tau^2 \end{aligned} \tag{15}$$

and find the minimum H_∞ performance γ^* by $\gamma^* = \sqrt{\frac{\nu^*(N+1)(1-\lambda_a)}{1-\lambda_b/\lambda}}$.

IV. Illustrative Example

Consider the satellite yaw angles control system with noise as studied in [13] and [27]. The satellite yaw angles control system consists of two rigid bodies joined by a flexible link. This link is modeled as a spring with torque constant k and viscous damping f. Let θ_1 and θ_2 denote, respectively, the yaw angles for the main body and the instrumentation module of the satellite, $\delta_1 = \dot{\theta}_1$ and $\delta_2 = \dot{\theta}_2$. $u(t)$ is the control torque, J_1 and J_2 are the moments of the main body and the instrumentation module, respectively. In presence of the unknown disturbance, the state-space representation of this control system is given by

$$E_c\dot{x}(t) = A_c x(t) + B_{1c}u(t) + B_{2c}w(t) \tag{16}$$

where,

$$E_c = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & J_1 & 0 \\ 0 & 0 & 0 & J_2 \end{bmatrix}, A_c = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ -k & k & -f & f \\ k & -k & f & -f \end{bmatrix}, \ B_{1c} = \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix}, B_{2c} = \begin{bmatrix} 0 \\ 0.1 \\ 0 \\ 0.1 \end{bmatrix}, \text{ and } x(t) = \begin{bmatrix} \theta_1(t) \\ \theta_2(t) \\ \delta_1(t) \\ \delta_2(t) \end{bmatrix}.$$

As in [13], we choose $J_1 = J_2 = 1, k = 0.3, f = 0.004$, the sampling period $T = 0.1s$, and use the controller $u(k) = 10^3 \begin{bmatrix} -0.1591 & -5.9343 & -0.0172 & -2.8604 \end{bmatrix} x(k)$. The resulting system is written as in (1) with

$$A = \begin{bmatrix} 0.2035 & -29.6580 & 0.0142 & -14.2960 \\ 0.0012 & 0.9871 & 0 & 0.0944 \\ -15.9256 & -592.9813 & -0.7168 & -285.8330 \\ 0.0188 & -0.4451 & 0.0007 & 0.7980 \end{bmatrix}, \ B = \begin{bmatrix} 0.000005189 \\ 0.01049 \\ 0.0001569 \\ 0.009843 \end{bmatrix}.$$

In this example, we aim to estimate $z(k) = Lx(k)$ by using two noisy measurements $y_p(k) = C_p x(k) + D_p w(k), p = 1, 2$, where $L = \begin{bmatrix} 1 & 1 & 0 & 0 \end{bmatrix}$, $C_1 = \begin{bmatrix} 1 & 0 & 0 & 0 \end{bmatrix}$, $C_2 = \begin{bmatrix} 0 & 1 & 0 & 0 \end{bmatrix}$, $D_1 = 0.5$ and $D_2 = 0.6$. Suppose that the two measurements are transmitted to the remote filter via two communication channels. In the first channel, the measurement signal may be delayed for one time step or can be transmitted instantly, that is $N_1 \in \{0, 1\}$. While, in the second channel, the measurement signal is always delayed for one time step, i.e., $N_2 \in \{1\}$. It is seen that the two channel conditions are different and the delay sequences are randomly generated in the latter simulation. In this example, we consider the Type I perturbation in the filter gains, and uncertain matrices are

$$M_1 = \begin{bmatrix} 0.1 & 0.2 & 0.1 & 0.1 \end{bmatrix}^T, \; M_2 = \begin{bmatrix} 0.1 & 0.1 & 0.2 & 0.1 \\ 0.2 & 0.1 & 0.1 & 0.1 \end{bmatrix}^T, \; M_3 = 0.2,$$

$$N_1 = \begin{bmatrix} 0.2 & 0.1 & 0.2 & 0.1 \end{bmatrix}, N_2 = \begin{bmatrix} 0.1 & 0.1 \\ 0.2 & 0.1 \end{bmatrix}, N_3 = \begin{bmatrix} 0.1 & -0.1 & 0.2 & 0.1 \end{bmatrix}.$$

The occurrence probability of the filter gain change is assumed to be $\bar{\alpha}_1 = 0.2$, and the amplitudes are $\delta_1 = 0.8, \delta_2 = 0.9, \delta_3 = 1.1$. Choosing $\lambda_1 = 0.91$, $\lambda_2 = 0.92$, $\lambda_b = 0.93$ and $\mu = 1.05$, we have $T_a^* = 0.6723 < 1$. Then, it follows that the optimal compensation scales are $r_{11} = 0.1$ and $r_{12} = 0.1$, the H_∞ performance is $\gamma^* = 5.1643$. It should be pointed out that, by using the delayed measurement directly, i.e., setting $r_{11} = r_{12} = 1$, the H_∞ performance is obtained as $\gamma^* = 5.3721$. Clearly, the new compensation scheme has reduced the design conservatism.

In the simulation setup, we choose the zero initial conditions for system (17) and filter (6), the uncertainties are chosen as $\Delta_1(k) = 0.8\sin(k)$, $\Delta_2(k) = 0.9\cos(k)$ and $\Delta_3(k) = 1.1 * rand[-1, 1]$. The unknown disturbance $w(k)$ is taken as

$$w(k) = \begin{cases} rand[0, 1], 10 \le k \le 40 \\ 0, \; others \end{cases} \tag{17}$$

The trajectories of $z(k)$ and $z_f(k)$ are shown in Fig. 1 based on our compensation technique. By simple calculation, we have $\sqrt{\sum_{k=0}^{100} e^T(k)e(k) \Big/ \sum_{k=0}^{100} w^T(k)w(k)} = 0.5540 < \gamma^* = 5.1643$.

To find the relation between the occurrence probability $\bar{\alpha}_1$ and the filtering performance γ^*, we vary $\bar{\alpha}_1$ and the results are shown in Table 1. It is seen that the less frequently the uncertainty occurs, the better filtering performance is. Hence, one may obtain very poor filtering performance if assuming the uncertainties occur for all the time, which is not the true in practice.

Table 1. Relation between $\bar{\alpha}_1$ and γ^*

$\bar{\alpha}_1$	0.1	0.2	0.3	0.4	0.5	0.6
γ^*	5.0763	5.1631	5.2265	5.2842	5.3382	5.3897

V. Conclusions

We have investigated the non-fragile filtering for a class of networked systems with distributed variable delays and random filter gain changes. A sufficient condition is derived such that a non-fragile filter

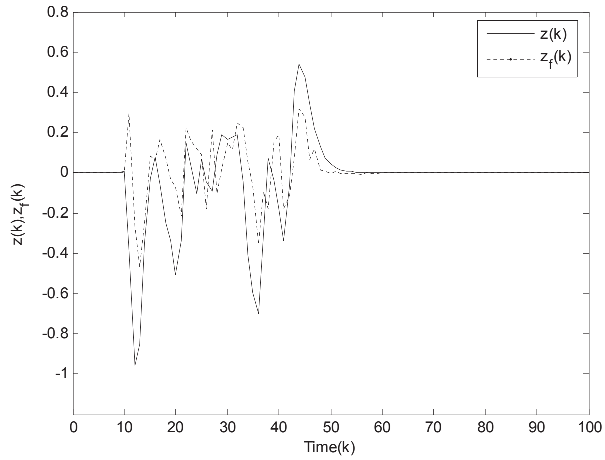

Fig. 1. The trajectories of $z(k)$ and $z_f(k)$

solution exists, and the filter gain design is also proposed. The quantitative relation between the filtering performance and the communication delay is established. The effectiveness of the proposed filter design is shown by a satellite yaw angles control system. To conclude the whole paper, it has the following merits:

- a switched system approach has been used to model the multiple variable delays, which keeps the properties of different channels and enables us to design the mode-dependent filter for each delay pattern.
- a simple yet effective method has been proposed to compensate the delayed information, while the existing results used the delayed information directly to design the filter.
- the first attempt has been made to study the random filter gain change problem, and the relations between the occurrence probability, uncertain bound and the filtering performance are established.
- unlike the existing works studied the additive and multiplicative filter gain change problems separately, these two issues have been studied in a unified work in this paper, and the filter gains are determined by solving a set of linear matrix inequalities, which is numerical efficient.

VI. Appendix

We only prove the stability of the filtering error system (8) in the presence of Type I gain perturbation, and one may follow the similar proof to obtain the results on Type II case. Construct the following

Lyapunov function for system (8):

$$V_i(k) = x^T(k)P_i x(k) \tag{18}$$

Then it follows that $\forall i \in \Gamma$,

$$\begin{aligned}
&\mathbb{E}\left\{V_i(k+1) - \lambda_i V_i(k) + \Upsilon(k)\right\} \\
&= \left[\tilde{A}_i\eta(k) + \tilde{B}_i W(k)\right]^T P_i \left[\tilde{A}_i\eta(k) + \tilde{B}_i W(k)\right] \\
&+\theta_1^2 \left[\tilde{D}_{1i}\eta(k) + \tilde{D}_{2i} W(k)\right]^T P_i \left[\tilde{M}_{1i}\eta(k) + \tilde{M}_{2i} W(k)\right] \\
&+ \left[\tilde{C}_i\eta(k)\right]^T \left[\tilde{C}_i\eta(k)\right] + \theta_1^2 \left[\tilde{N}_{3i}\eta(k)\right]^T \left[\tilde{N}_{3i}\eta(k)\right] \\
&-\lambda_i\eta^T(k)P_i\eta(k) - \tau^2 W^T(k)W(k)
\end{aligned} \tag{19}$$

where, $\Upsilon(k) = e^T(k)e(k) - \tau^2 W^T(k)W(k)$. By arrangement, it is easy to see $\mathbb{E}\left\{V_i(k+1) - \lambda_i V_i(k) + \Upsilon(k)\right\} < 0$ is equivalent to

$$\Phi_1 + \Phi_2\Delta(k)\Phi_3^T + \Phi_3^T\Delta(k)\Phi_2 < 0 \tag{20}$$

where

$$\Phi_1 = \begin{bmatrix} -\lambda_i P_i & 0 & \bar{A}_i^T & 0 & \bar{C}_i^T & 0 \\ * & -\tau^2 I & \bar{B}_i^T & 0 & 0 & 0 \\ * & * & -P_i^{-1} & 0 & 0 & 0 \\ * & * & * & -P_i^{-1} & 0 & 0 \\ * & * & * & * & -I & 0 \\ * & * & * & * & * & -I \end{bmatrix}, \ \Phi_2 = \begin{bmatrix} \bar{N}_{1i}^T & \bar{N}_3^T \\ \bar{N}_{2i}^T & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}, \Phi_3 = \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ \bar{\alpha}_1\bar{M}_i & 0 \\ \theta_1\bar{M}_i & 0 \\ 0 & \bar{\alpha}_1\tilde{M}_{3i} \\ 0 & \theta_1\tilde{M}_{3i} \end{bmatrix},$$

$$\Delta(k) = \operatorname{diag}\left\{\bar{\Delta}_1(k), \Delta_3(k)\right\}.$$

It follows from Lemma 1 that (20) holds if and only if (11) holds. Hence, $\mathbb{E}\left\{V_i(k+1) - \lambda_i V_i(k) + \Upsilon(k)\right\} < 0$. For the switching time instant $k_0 < k_1 < \cdots < k_i < \cdots < k_s$, one has

$$\mathbb{E}\{V_i(k)\} \leq \mathbb{E}\{\lambda_i^{k-k_i} V_i(k_i)\} - \sum_{s=k_i}^{k-1} \lambda_i^{k-s-1}\mathbb{E}\{\Upsilon(s)\} \tag{21}$$

It follows from (12) and (21) that

$$\begin{aligned}
&\mathbb{E}\{V_{\sigma(k_l)}(k)\}\\
&\le \lambda_{\sigma(k_l)}^{k-k_l}\mathbb{E}\{V_{\sigma(k_l)}(k_l)\} - \sum_{s=k_l}^{k-1}\lambda_{\sigma(k_l)}^{k-s-1}\mathbb{E}\{\Upsilon(s)\}\\
&\le \lambda_{\sigma(k_l)}^{k-k_l}\mu\mathbb{E}\{V_{\sigma(k_{l-1})}(k_l)\} - \sum_{s=k_l}^{k-1}\lambda_{\sigma(k_l)}^{k-s-1}\mathbb{E}\{\Upsilon(s)\}\\
&\le \lambda_{\sigma(k_l)}^{k-k_l}\mu\left[\lambda_{\sigma(k_{l-1})}^{k_l-k_{l-1}}\mathbb{E}\{V_{\sigma(k_{l-1})}(k_{l-1})\} - \sum_{s=k_{l-1}}^{k_l-1}\lambda_{\sigma(k_{l-1})}^{k-s-1}\mathbb{E}\{\Upsilon(s)\}\right]\\
&\quad - \sum_{s=k_l}^{k-1}\lambda_{\sigma(k_l)}^{k-s-1}\mathbb{E}\{\Upsilon(s)\}\\
&\le \cdots \le \mu^{N_\sigma(k_0,k)}\lambda_{\sigma(k_l)}^{k-k_l}\lambda_{\sigma(k_{l-1})}^{k_l-k_{l-1}}\cdots\lambda_{\sigma(k_0)}^{k_1-k_0}V_{\sigma(k_0)}(k_0) - \Theta(\Upsilon)
\end{aligned} \tag{22}$$

where

$$\begin{aligned}
\Theta(\Upsilon) &= \mu^{N_\sigma(k_0,k-1)}\lambda_{\sigma(k_l)}^{k-k_l}\prod_{s=1}^{l-1}\lambda_{\sigma(k_s)}^{k_{s+1}-k_s}\sum_{s=k_0}^{k_1-1}\lambda_{\sigma(k_0)}^{k_1-1-s}\mathbb{E}\{\Upsilon(s)\}\\
&\quad+\mu^{N_\sigma(k_0,k-1)-1}\lambda_{\sigma(k_l)}^{k-k_l}\prod_{s=2}^{l-1}\lambda_{\sigma(k_j)}^{k_{j+1}-k_j}\sum_{s=k_1}^{k_2-1}\lambda_{\sigma(k_1)}^{k_2-1-s}\mathbb{E}\{\Upsilon(s)\}\\
&\quad+\cdots+\mu^0\prod_{s=k_l}^{k-1}\lambda_{\sigma(k_l)}^{k-1-s}\mathbb{E}\{\Upsilon(s)\}.
\end{aligned}$$

Now, we consider the exponential stability of system (8) with $W(k) = 0$. One has

$$\begin{aligned}
&\mathbb{E}\{V_{\sigma(k_l)}(k)\}\\
&\le \mu^{N_\sigma(k_0,k)}\lambda_{\sigma(k_l)}^{k-k_l}\lambda_{\sigma(k_{l-1})}^{k_l-k_{l-1}}\cdots\lambda_{\sigma(k_0)}^{k_1-k_0}V_{\sigma(k_0)}(k_0)\\
&\le \mu^{N_\sigma(k_0,k)}\lambda_b^{k-k_0}V_{\sigma(k_0)}(k_0)\\
&\le \left(\mu^{1/T_a}\lambda_b\right)^{k-k_0}V_{\sigma(k_0)}(k_0) = \chi^{2(k-k_0)}V_{\sigma(k_0)}(k_0)
\end{aligned} \tag{23}$$

which yields $\left\{\|\eta(k)\|^2\right\} \le \frac{\varphi_2}{\varphi_1}\chi^{2(k-k_0)}\|\eta(k_0)\|^2$, where $\varphi_1 = \min_{i\in\Gamma}\sigma_{\min}(P_i)$, $\varphi_2 = \max_{i\in\Gamma}\sigma_{\max}(P_i)$, $\chi = \sqrt{\lambda_b\mu^{1/T_a}}$. Therefore, one can readily obtain $\chi < 1$ from condition (13). According to Definition 2, the filtering error system (8) is exponentially stable in the mean-square sense with $W(k) = 0$.

For H_∞ performance level, we consider $W(k) \neq 0$. Under zero initial condition, it follows from (22) that

$$\sum_{s=k_0}^{k-1}\mu^{N_\sigma(s,k-1)}\lambda_a^{k-s-1}\mathbb{E}\{e^T(s)e(s)\} \le \tau^2\sum_{s=k_0}^{k-1}\mu^{N(s,k-1)}\lambda_b^{k-s-1}W^T(s)W(s) \tag{24}$$

With the average dwell time condition (13), it is easy to see $\frac{N_\sigma(s,k-1)}{k-s-1} < -\frac{\ln\lambda}{\ln\mu}$. Since $\mu > 1$, we obtain $\ln\mu^{N_\sigma(s,k-1)} < \ln\lambda^{-(k-s-1)}$, and $1 < \mu^{N_\sigma(s,k-1)} < \lambda^{-(k-s-1)}$. Then, it can be readily seen that

$$\sum_{s=k_0}^{k-1}\lambda_a^{k-s-1}\mathbb{E}\{e^T(s)e(s)\} < \tau^2\sum_{s=k_0}^{k-1}(\lambda_b/\lambda)^{k-s-1}\lambda^{k-s-1}W^T(s)W(s) \tag{25}$$

Summing (25) from $k = k_0 + 1$ to $k = \infty$ and changing the order of summation yields

$$\sum_{s=k_0}^{+\infty}\mathbb{E}\{e^T(s)e(s)\}\sum_{k=s+1}^{+\infty}\lambda_a^{k-s-1} < \tau^2\sum_{s=k_0}^{+\infty}W^T(s)W(s)\sum_{k=s+1}^{+\infty}(\lambda_b/\lambda)^{k-s-1} \tag{26}$$

Since $\sum_{k=s+1}^{+\infty} \lambda_a^{k-s-1} = \frac{1}{1-\lambda_a}$ and $\sum_{k=s+1}^{+\infty} (\lambda_b/\lambda)^{k-s-1} = \frac{1}{1-(\lambda_b/\lambda)}$, we have

$$\sum_{s=k_0}^{+\infty} \mathbb{E}\{e^T(s)e(s)\} < \tilde{\gamma}^2 \sum_{s=k_0}^{+\infty} W^T(s)W(s) \tag{27}$$

where $\tilde{\gamma} = \tau\sqrt{\frac{1-\lambda_a}{1-\lambda_b/\lambda}}$. It is noted that $\lambda_b < \lambda$, which ensures $\tilde{\gamma} > 0$. Let $k_0 = 0$, one has $\sum_{s=0}^{+\infty} \mathbb{E}\{e^T(s)e(s)\} \leq \tilde{\gamma}^2 \sum_{s=0}^{+\infty} W^T(s)W(s) = \gamma^2 \sum_{s=0}^{+\infty} w^T(s)w(s)$, where, $\gamma^2 = (N+1)\tilde{\gamma}^2$. This completes the proof.

References

[1] A. Liu, L. Yu, and W. Zhang, "H_∞ control for network-based systems with time-varying delay and packet disordering ," J. Franlin. Inst., vol. 348, no. 5, 917-932, 2011.

[2] L.Q. Zhang, Y. Shi, T. W. Chen, and B. Huang, "A new method for stabilization of networked control systems with random delays," IEEE Trans. Autom. Control, vol. 50, no. 8, pp. 1177-1181, 2005.

[3] Z.D. Wang, D.W.C. Ho, Y.R. Liu, and X.H. Liu, "Robust H_∞ control for a class of nonlinear discrete time-delay stochastic systems with missing measurements," Automatica, vol. 45, no. 3, pp. 684-691, 2009.

[4] Y. Xu, H. Su, Y. Pan, Z. Wu, and W. Xu, "Stability analysis of networked control systems with round-robin scheduling and packet dropouts," J. Franklin. Inst., vol. 350, no. 8, pp. 2013-2027, 2013.

[5] M.Y. Fu, and L.H. Xie, "The sector bound approach to quantized feedback control," IEEE Trans. on Autom. Control., vol. 50, no. 11, pp. 1698-1711, 2005.

[6] J. P. Hespanha, P. Naghshtabrizi, and Y. Xu, "A survey of recent results in networked control systems," Proc. IEEE, vol. 95, no. 1, pp. 138-162, 2007.

[7] L. Zhang, H. Gao, and O. Kaynak, "Network-Induced Constraints in Networked Control System-A Survey," IEEE Trans. Ind. Inform., vol. 9, no. 1, pp. 403-416, 2013.

[8] D. Yue, and Q.L. Han, "Network-based robust H_∞ filtering for uncertain linear system," IEEE Trans. Signal Process., vol. 54, no. 11, pp. 4293-4301, 2006.

[9] D. Zhang, Q.G. Wang, L. Yu, and H.Y. Song,"Fuzzy-Model-Based Fault Detection for a Class of Nonlinear Systems With Networked Measurements," IEEE Trans. Instru. Meas., vol. 62, no. 12, pp. 3148-3159, 2013.

[10] X. Zhang, and Q. Han, "Network-based H_∞ filtering using a logic jumping-like trigger," Automatica, vol. 49, no. 5, pp. 1428-1435, 2013.

[11] P. Shi, X. Luan, and F. Liu, "H_∞ filtering for discrete-time systems with stochastic incomplete measurement and mixed delays," IEEE Trans. Ind. Electron., vol. 59, no. 6, pp. 2732-2739, 2012.

[12] Y. Xu, H. Su, Y. Pan, and Z. Wu, "Robust H_∞ filtering for networked stochastic systems with randomly occurring sensor nonlinearities and packet dropouts," Signal Process., vol. 93, no. 7, pp. 1794-1803, 2013.

[13] W. Zhang, L. Yu, and H. Song, "H_∞ filtering of networked discrete-time systems with random packet losses," Inform. Sciences., vol. 179, no. 22, pp. 3944-3955, 2009.

[14] Y. Zhang, Z. Liu, H. Fang, and H. Chen, "H_∞ fault detection for nonlinear networked systems with multiple channels data transmission pattern," Inform. Sciences., vol. 221, pp. 534-543, 2013.

[15] M.S. Mahmoud, "Resilient linear filtering of uncertain systems," Automatica, vol. 40, no. 10, pp. 1797-1802, 2004.

[16] X. Chang, and G. Yang, "Non-fragile fuzzy H_∞ filter design for nonlinear continuous-time systems with D stability constraints," Signal Process., vol. 92, no. 2, pp. 575-586, 2012.

[17] X. Chang, and G. Yang, "Non-fragile H_∞ filter design for discrete-time fuzzy systems with multiplicative gain variations," Inform. Sciences, in press.

[18] J. Zhang, P. Shi, and J. Qiu., "Non-fragile guaranteed cost control for uncertain stochastic nonlinear time-delay systems ," J. Franklin. Inst., vol. 346, no. 7, pp. 676-690, 2009.

[19] W. Che, G. Yang, and X. Jin., "Non-fragile H_∞ filter design with sparse structure for linear discrete-time systems," J. Franklin. Inst., in press.

[20] D. Liberzon, Switching in Systems and Control. Boston, MA: Birkhauser, 2003.

[21] X. Sun, G. Liu, W. Wang, and D. Rees., "Stability analysis for networked control systems based on average dwell time method," Int. J. Robust Nonlinear Control., vol. 20, no. 15, pp. 1774-1784, 2010.

[22] W. Zhang, L. Yu, and S. Yin., "A switched system approach to H_∞ control of networked control systems with time-varying delays," J. Franklin. Inst., vol. 348, no. 2, pp. 165-178, 2011.

[23] X. Sun, J. Zhao, and D.J. Hill., "Stability and L_2-gain analysis for switched delay systems: A delay-dependent method," Automatica., vol. 42, no. 10, pp. 1769-1774, 2006.

[24] L. Zhang, E. Boukas, and P. Shi, "Exponential H_∞ Filtering for Uncertain Discrete-Time Switched Linear Systems with Average Dwell Time: A μ-Dependent Approach," Int. J. Robust. Nonlinear. Contr., vol. 18, no. 11, pp. 1188-1207, 2008.

[25] L. Wu, and W.X. Zheng, "Weighted H_∞ model reduction for linear switched systems with time-varying delay," Automatica, vol. 45, no. 1, pp. 186-193, 2009.

[26] D. Zhang, L. Yu, and W. Zhang, "Delay-dependent fault detection for switched linear systems with time-varying delays-the average dwell time approach," Signal Process., vol. 91, no. 4, pp. 832-840, 2011.

[27] H.J. Gao, J. Lam, T.W. Chen, and C.H. Wang, "Feedback control with signal transmission after-effects, Int. J. Robust Nonlinear Control., vol. 18, no. 3, pp. 351-363, 2008.