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Event-Triggered Dissipative Filtering for Network-Based Stochastic Genetic Regulatory Networks Under Aperiodic Sampling

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ABSTRACT Based on event-triggered mechanism, networked dissipative filtering of stochastic genetic regulatory networks is investigated under aperiodic sampling. The states of the genetic regulatory network are sampled aperiodically and transmitted via a communication network to filters to estimate the expression levels of the mRNA and protein. In order to make better use of limited communication resources, a novel communication scheme is proposed. Then considering both network-induced delays and aperiodic sampling simultaneously, the filtering error dynamics are modeled in the form of a stochastic system with a time-varying delay. By Lyapunov theory and Wirtinger-based integral inequalities in a stochastic setting, asymptotical stability and dissipativity of the error dynamic system can be ensured. Based on the derived criterion, suitable dissipative filters are designed such that a set of inequalities are satisfied. Finally, the effectiveness of the proposed method is illustrated by a simulation example.

INDEX TERMS Aperiodic sampling, event-triggered scheme, dissipative filtering, genetic regulatory networks, transmission delays.

I. INTRODUCTION

Genetic regulatory networks (GRNs), a kind of mechanisms used to express the interactions between genes (mRNA) and their products (proteins), have been attracted tremendous attention due not only to the extensive engineering applications, but also to the theoretical research interest in biomedical. Over the past few decades, numerous effort has been devoted to the field of GRNs, see as in [1]–[3] and references therein. In [2], [3], a stochastic nonlinear dynamic model has been developed for GRNs under random intra- and inter-cellular fluctuations. Besides, it is well known that a number of applications of GRNs heavily depend on neuron states in order to identify genes of interest and design drugs. However, in practice, due to the inherent internal random fluctuations or the external noises, only parts of neuron states may be available in network outputs. Thus, neuron state estimation of GRNs has attracted enormous attention, and substantial effort has been made on this topic, see for example, [3]–[9]. In [4], a stochastic nonlinear dynamic model has been developed for GRNs, and a sampled data filtering method has been proposed to estimate the states of the genetic network. Chen *et al.* [9] investigates H_∞ filtering for Markovian switching genetic regulatory networks with time-delays and stochastic disturbances.

Although many algorithms for GRNs have been proposed in the literature, it is worth mentioning that most aforementioned results are developed to solve a point-to-point architecture, which requires continual and instantaneous communication between the GRN and the filter. Such a pattern may be unrealistic or even fail to perform filtering tasks in many practical circumstances. For example, in [3], conventional filtering based on continual communication is no longer applicable if the measurement is sampled and digital. With the rapid advancement and progress in the field of the computer industry and artificial intelligence, network-based control has been widely used in engineering, biological science, social science and other areas. Using communication networks to transmit data can potentially improve the reliability and scalability of GRNs, but the communication load and bandwidth are always limited. Thus it is significant to find an effective control scheme to save communication resources while preserving

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the desired filtering performance, see as in [10]–[14] and references therein. Recently, some transmission strategies, such as event-triggered schemes, have been proposed to tradeoff the communication resources and system performance. A number of results are focused on the state estimation of GRNs under network environments [15]–[18], while most of them are in discrete settings and not considering network resources. It is essential to develop a network-based strategy for filtering of GRNs regarding communication resources, which is the initial motivation of the current study.

Since dissipativity concept was first proposed in [19], it has attracted much researchers' attention. Dissipativity is a generalization of passivity and H_∞ property [20]. It has been popularly utilised in electrical circuits, mechanical systems, industry, viscoelastic materials, and so on. A variety of results on dissipative filtering for network-based neural networks have been developed. For example, network-based dissipative filtering for neural networks is investigated in [21]. However, the physical plant is a deterministic system rather than a stochastic system. In [22], the quantized asynchronous dissipative state estimation of Markovian jumping neural networks is studied while the plant is assumed to be discrete-time. When the physical plant is a stochastic continuous-time system and the sampling is aperiodic, the criteria on dissipative filtering techniques in [21] and [22] may not be effective. To the best of authors' knowledge, few results on the dissipative filtering of GRNs under aperiodic sampling have been published, which is the second motivation of this study.

Motivated by the above discussion, in order to make research more realistic, in this paper, we investigate event-triggered networked dissipative filtering of a genetic regulatory network. The signal transmitted from a GRN to its filter through a communication channel where the signal is sampled aperiodically. The event-triggered scheme is first introduced to the research of filtering of GRNs. Compared with the existing results of GRNs, the proposed mechanism in this paper is more realistic and can significantly reduce the communication load and maintain the filtering performance. Based on the proposed event-triggered scheme, a new framework incorporating network-induced delays and aperiodic sampling is developed. Then the filtering error system is modeled as a time-delay sampled-data error dependent stochastic system. By the Wirtinger-based inequalities in stochastic setting, suitable filters can be designed such that certain filtering performances can be ensured. Finally, the effectiveness of the proposed method is shown by a simulation example.

Notations: In this paper, diag$\{\cdots\}$ and col$\{\cdots\}$ represent a diagonal matrix and a column vector, respectively. The symbol He$\{A\}$ means $A+A^T$. The space of square-integrable vector functions over $[0,\infty)$ is denoted by $\mathcal{L}_2[0,\infty)$. The symbol '$\star$' stands for the symmetric term in a symmetric matrix.

II. PROBLEM DESCRIPTION

Consider a genetic regulatory network (GRN) described by

$$\begin{cases} \dfrac{dm(t)}{dt} = -Am(t) + Bg(p(t)) + E_m v(t) + l \\ \dfrac{dp(t)}{dt} = -Cp(t) + Dm(t) + E_p v(t) \end{cases} \tag{1}$$

where

$$\begin{aligned} m(t) &= \left[m_1(t)\ m_2(t)\ \cdots\ m_n(t)\right], \\ p(t) &= \left[p_1(t)\ p_2(t)\ \cdots\ p_n(t)\right], \\ A &= \mathrm{diag}(a_1, a_2, \cdots, a_n), \\ C &= \mathrm{diag}(c_1, c_2, \cdots, c_n), \\ D &= \mathrm{diag}(d_1, d_2, \cdots, d_n), \\ E_m &= \left[e_{m1}, e_{m2}, \cdots, e_{mn}\right]^T, \\ E_p &= \left[e_{p1}, e_{p2}, \cdots, e_{pn}\right]^T, \\ l &= \left[l_1, l_2, \cdots, l_n\right]^T, \\ g(p(t)) &= \left[g_1(p_1(t)), g_2(p_2(t)), \cdots, g_n(p_n(t))\right]^T. \end{aligned}$$

with $i = 1, 2, \cdots, n$, $m_i(t)$ and $p_i(t)$ representing the concentrations of mRNA and protein of the ith gene at time t, respectively; a_i and c_i are the degradation rates of mRNA and protein, respectively; d_i denotes the translation rate. The function $g_j(\cdot)$ is a nonlinear function. The matrix $B = (b_{ij})_{n\times n}$ is the coupling matrix of the genetic network defined as: if transcription factor j is an activator of gene i, then $b_{ij} = a_{ij}$; if no connection exists between j and i, then $b_{ij} = 0$; if transcription factor j is a repressor of gene i, then $b_{ij} = -a_{ij}$, where a_{ij} is a positive scalar which denotes the transcriptional rate of transcription factor j to gene i. l_i is a basal rate; $v(t)$ represents the exogenous disturbance belonging to $\mathcal{L}_2[0\ \infty)$; e_{mi} and e_{pi} characterize the intensities of the exogenous disturbance to the mRNA and the protein, respectively. Denote the equilibrium point of the system (1) as $\left[m^{*T}\ p^{*T}\right]^T \in \mathbb{R}^{2n}$, and shift it to the origin and obtain the following system

$$\begin{cases} \dfrac{d\bar{m}(t)}{dt} = -A\bar{m}(t) + Bf(\bar{p}(t)) + E_m v(t) \\ \dfrac{d\bar{p}(t)}{dt} = -C\bar{p}(t) + D\bar{m}(t) + E_p v(t) \end{cases} \tag{2}$$

where $f(\bar{p}(t))$ satisfies

$$f(\bar{p})(f(\bar{p}) - F\bar{p}) \leq 0, \quad \forall \bar{p} \in \mathbb{R}^n \tag{3}$$

with $F = \mathrm{diag}\{k_1, k_2, \cdots, k_n\}$.

Due to intrinsic and stochastic fluctuations in the gene regulation process, genetic networks can be modified as

$$\begin{cases} d\bar{m}(t) = [-A\bar{m}(t) + Bf(\bar{p}(t)) + E_m v(t)]dt \\ \qquad\qquad + g_m(\bar{m}(t))dw_m(t) \\ d\bar{p}(t) = [-C\bar{p}(t) + D\bar{m}(t) + E_p v(t)]dt \\ \qquad\qquad + g_p(\bar{p}(t))dw_p(t) \end{cases} \tag{4}$$

where the initial values of $\bar{m}(0)$ and $\bar{p}(0)$ are assumed to be $\mathcal{F}_0$-measurable bounded random variables;

$w_m(t) = [w_{m1}(t)\ w_{m2}(t) \cdots\ w_{mn}(t)]^T$ and $w_p(t) = [w_{m1}(t)\ w_{m2}(t) \cdots\ w_{mn}(t)]^T$ are n-dimensional Brownian motions in the probability space$(\Omega, \mathcal{F}, \mathcal{F}_{t\le 0}, P)$; the intensity functions $g_m(\bar{m}(t))$, $g_p(\bar{p}(t))$ are satisfied

$$g_m^T(\bar{m}(t))g_m(\bar{m}(t)) \le \bar{m}^T(t)G_m\bar{m}(t), \tag{5}$$

$$g_p^T(\bar{p}(t))g_p(\bar{p}(t)) \le \bar{p}^T(t)G_p\bar{p}(t) \tag{6}$$

where G_m and G_p are known matrices.

In some practical genetic networks, biologists need to obtain the concentrations of the proteins and the mRNAs of the GRNs, such as designing and developing proper drugs. However, the existence of disturbance, time delays, stochastic noises and parameter uncertainties makes it difficult to obtain the accurate state values of GRNs, which gives rise to the motivation of filtering of GRNs. In this paper, the expression levels of mRNAs and proteins are described as follows:

$$y(t) = L_m\bar{m}(t) + L_p\bar{p}(t) \tag{7}$$

where $y(t) \in \mathbb{R}^q$, $(q < n)$ represents the expression levels of mRNAs and proteins at time instant t. L_m and L_p are two known measurement matrices.

To simplify the analysis, a new vector $x(t) = [\bar{m}^T(t)\ \bar{p}^T(t)]^T$ is defined. Accordingly, the system (4) with measurements in (7) becomes

$$\begin{cases} dx(t) = [-\tilde{A}x(t) + \tilde{B}\tilde{f}(x(t)) + \tilde{E}v(t)]dt \\ \qquad\quad + \tilde{g}(x(t))dw(t) \\ y(t) = C_1x(t) \\ z(t) = C_2x(t) \end{cases} \tag{8}$$

with

$$\tilde{A} = \begin{bmatrix} A & 0 \\ -D & C \end{bmatrix}, \quad \tilde{B} = \begin{bmatrix} B \\ 0 \end{bmatrix}, \ \tilde{E} = \begin{bmatrix} E_m \\ E_p \end{bmatrix},$$
$$C_1 = \begin{bmatrix} L_m\ L_p \end{bmatrix},$$
$$w(t) = \begin{bmatrix} w_m(t) & w_p(t) \end{bmatrix}^T, \tilde{f}(x(t)) = f(\bar{p}(t)),$$
$$\tilde{g}(x(t)) = \mathrm{diag}\{g_m(\bar{m}(t)), g_p(\bar{p}(t))\}.$$

where $z(t)$ is the signal to be estimated where C_2 is the known real constant matrix with compatible dimension. From (3) and (5), one can obtain that the nonlinear functions $\tilde{f}(x(t))$ and $\tilde{g}(x(t))$ satisfy

$$\begin{cases} \tilde{f}^T(x(t))(\tilde{f}(x(t)) - Fx(t)) \le 0, \\ \tilde{g}^T(x(t))(\tilde{g}(x(t)) \le x^T(t)\tilde{G}x(t) \end{cases} \tag{9}$$

The objective of the paper is to design suitable filters to estimate the actual states of mRNAs and proteins based on the measured signal $y(t)$. As shown in Fig. 1, the filter and the GRN are located in different places, signals transmitted between each other through network. In this situation, the input signal of the filter $\tilde{y}(t)$ is no longer equal to the measurement $y(t)$, so the existing filtering methods as in [3], [7], [8], are not applicable. In this paper, we propose a novel method to solve the networked filtering of the GRN (1).

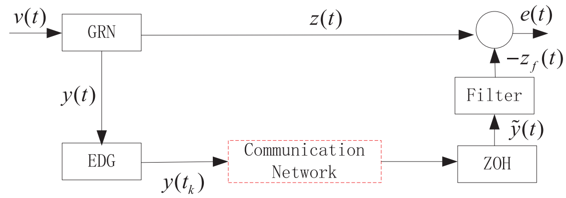

FIGURE 1. The diagram of event-triggered network-based dissipative filtering for a GRN.

A. AN APERIODIC SAMPLED-DATA EVENT-TRIGGERED COMMUNICATION SCHEME

In Fig. 1, the measurement signal $y(t)$ is first sampled at aperiodic discrete instants $\{s_k|s_k \in \mathbb{R}; k \in \mathbb{R}\}$ satisfying

$$\begin{cases} 0 = s_0 < s_1 < s_2 < \cdots < s_k < \ldots, \ \lim_{k\to\infty} s_k = \infty \\ 0 \le \underline{h} \le h_k = s_{k+1} - s_k \le \bar{h} \end{cases}$$

where $\underline{h}$ and $\bar{h}$ are the lower and upper bounds of the uncertain sampling interval h_k, respectively.

The sampled measurement with its time stamp $(s_k, y(s_k))$ is encapsulated into a data packet. Whether or not the sampled data will be transmitted is selected arbitrarily by the event-triggered data generator (EDG). The triggering time sequence t_k is defined iteratively by:

$$t_{k+1} = \inf\{t|s(t) \ge 0\}, \tag{10}$$

where $s(t)$ is the event triggering function defined as

$$s(t) = \psi^T(t_{jk})\Omega\psi(t_{jk}) - \lambda y^T(t_k)\Omega y(t_k), \tag{11}$$

where $\psi(t_{jk}) = y(t_{jk}) - y(t_k)$; $\lambda \in (0, 1)$ is a threshold parameter; $\Omega > 0$ is triggering matrix to be determined. $y(t_k)$ is the transmitted data and $y(t_{jk})$ is the following sampled data. In this mechanism, assume that the initial sampled data $y(0)$ should be triggered.

Suppose the ZOH is event-driven. Once a data packet arrives at the ZOH, it immediately updates its store and actuates the filter, otherwise, ZOH keeps the previous data. The data packets released by the plant to the filter are unavoidably delayed due to the limited network bandwidth and/or congested network. The transmission delay τ_k of the released data packet $(t_k, y(t_k))$ from the plant to the filter is assumed to satisfy

$$\tau_m \le \tau_k \le \tau_M \le \underline{h} \tag{12}$$

where τ_m and τ_M are two constants.

Under the above assumptions, one can see that the time sequence, which indicates when the released data packets arrive at the ZOH, can be given as $t_1 + \tau_{t_1}, t_2 + \tau_{t_2}, \cdots, t_k + \tau_{t_k}, \cdots$ with $t_k + \tau_{t_k} < t_{k+1} + \tau_{t_{k+1}}$. Accordingly, one has

$$\tilde{y}(t) = y(t_k) \ \ t \in [t_k + \tau_{t_k}, t_{k+1} + \tau_{t_{k+1}}) \tag{13}$$

which is used to be the input signal of the filter. Denote $\Pi_k = [t_k + \tau_{t_k}, t_{k+1} + \tau_{t_{k+1}})$ and $l_k = t_{k+1} - t_k - 1$. Then $\Pi_k = \cup_{j=0}^{l_k}\Pi_{kj}$, where $\Pi_{kj} = [t_{kj} + \tau_{kj}, t_{k,(j+1)} + \tau_{k,(j+1)})$.

Define an artificial time delay $d(t) = t - t_{kj}$, $t \in \Pi_{kj}$. It is worthy noting that $d(t)$ is piecewise linear and discontinuous at $t = t_k$ with

$$d_m \triangleq \tau_m \leq d(t) \leq \underline{h} + \bar{h} \triangleq d_M, \dot{d}(t) = 1(t \neq t_k) \quad (14)$$

Then (13) can be rewritten as

$$\tilde{y}(t) = y(t - d(t)) - \psi(t - d(t)) \quad t \in [t_k + \tau_{t_k}, t_{k+1} + \tau_{t_{k+1}}) \quad (15)$$

Remark 1: Different from the exiting event-triggered schemes, the mechanism of the proposed event-triggered scheme in this paper is based on aperiodic sampling. The sampling period is not fixed but belongs to a range with a specific minimum period, which can be used to prevent the Zeno behavior. Periodic sampling is a specific case of this aperiodic sampling.

B. THE FILTER

In this paper, a full-order filter is to be designed in the form of

$$\begin{cases} \dfrac{dx_f(t)}{dt} = A_f x_f(t) + B_f \tilde{y}(t), & x_f(0) = 0 \\ z_f(t) = C_f x_f(t), & t \in [t_k + \tau_{t_k}, t_{k+1} + \tau_{t_{k+1}}) \end{cases} \quad (16)$$

where A_f, B_f and C_f are filter gain matrices to be determined. The input signal $\tilde{y}(t)$ is given in (15).

Substituting (15) into (16) yields

$$\begin{cases} \dfrac{dx_f(t)}{dt} = A_f x_f(t) + B_f y(t - d(t)) - B_f \psi(t - d(t)) \\ x_f(0) = 0 \\ z_f(t) = C_f x_f(t), \quad t \in [t_k + \tau_{t_k}, t_{k+1} + \tau_{t_{k+1}}) \end{cases} \quad (17)$$

To summarize, under the aperiodic sampling event-triggered communication scheme, the filter (16) can be rewritten as a time delay system as in (17).

C. PROBLEM FORMATION

Denote

$$\xi(t) := \mathrm{col}\{x(t), x_f(t)\}, \quad e(t) := z(t) - z_f(t)$$

Then, the filtering error system connecting the GRN (8) with the filter (17) can be described as

$$\begin{cases} d\xi(t) = [\bar{A}\xi(t) + \bar{B}\tilde{f}(x(t)) + \bar{B}_f H \xi(x(t - d(t))) \\ \qquad + \bar{B}_f \psi(t - d(t)) + \bar{E}v(t)]dt + \bar{g}(t)dw(t) \\ \xi(\theta) = \mathrm{col}\{\phi(\theta), 0\}, \ \theta \in [-h_M, \ 0] \\ e(t) = \bar{C}_2 \xi(t), \quad t \in [t_k + \tau_{t_k}, t_{k+1} + \tau_{t_{k+1}}) \end{cases} \quad (18)$$

where

$$\bar{A} = \mathrm{diag}\{-\tilde{A}, A_f\}, \bar{C}_2 = [C_2 \ \ -C_f], \bar{B}_f = \mathrm{col}\{0, B_f\},$$
$$\bar{B} = \mathrm{col}\{\tilde{B}, 0\}, \bar{E} = \mathrm{col}\{\tilde{E}, 0\}, \bar{g}(t) = \mathrm{col}\{\tilde{g}(t), 0\}, \bar{H} = [C_1 \ 0].$$

Next, we introduce a definition of dissipativity in stochastic setting.

Definition 1 (Dissipativity [20]): For given real matrices $\Psi_1 \leq 0$, Ψ_2 and $\Psi_3 > 0$, the filtering error system (18) is said to be dissipative, if under zero initial conditions, the following inequality holds for any $t \geq 0$ and $v \in \mathcal{L}_2[0, \infty)$,

$$J(t)dt \geq \mathscr{L}\{V(t) - V(0)\} \quad (19)$$

where

$$J(t) = e^T(t)\Psi_1 e(t) + 2e^T(t)\Psi_2 v(t) + v^T(t)\Psi_3 v(t) \quad (20)$$

The problem of dissipative filtering to be studied in this paper is formulated as: for given scalars d_m, d_M, design suitable filter gain matrices (A_f, B_f, C_f) such that

i) the filtering error system (18) with $v(t) \equiv 0$ is asymptotically stable; and
ii) the filtering error system (18) is dissipative in the sense of Definition 1.

To proceed further, we need to introduce two integral inequalities, which are useful in solving the above filtering problem.

Lemma 1 [14]: Consider the following stochastic differential equation

$$dx(t) = l(t)dt + g(t)dw(t) \quad (21)$$

where $w(t)$ is a one-dimensional Brownian motion. Then for $R \in \mathbb{R}^{n \times n}$ $(R > 0)$, and two scalars a and b satisfying $b > a$, one has

$$\int_a^b l^T(s)Rl(s)ds \geq \frac{1}{b-a}\nu^T(a, b)\tilde{R}\nu(a, b) + \frac{2}{b-a}\nu^T(a, b)\tilde{R}\beta(a, b) \quad (22)$$

where $\tilde{R} = \left[\begin{smallmatrix} R & 0 \\ 0 & 3R \end{smallmatrix}\right]$ and

$$\begin{aligned} \nu(a, b) &:= \mathrm{col}\{\nu_1, \nu_2\}, \quad \beta(a, b) := \mathrm{col}\{\beta_1, \beta_2\} \quad (23) \\ \nu_1 &:= x(b) - x(a), \quad \beta_1 := \textstyle\int_a^b g(s)dw(s) \\ \nu_2 &:= x(b) + x(a) - \tfrac{2}{b-a}\textstyle\int_a^b x(s)ds \\ \beta_2 &:= \tfrac{1}{b-a}\textstyle\int_a^b (b - a + 2s)g(s)dw(s) \end{aligned}$$

Lemma 2 [14]: Consider the stochastic differential equation (21). For $n \times n$ real matrix $R > 0$ and the piecewise function $\eta(t)$ satisfying $\eta_m \leq \eta(t) \leq \eta_M$, where η_m and η_M are two constants, $\bar{\eta} = \eta_M - \eta_m$ and for $S \in \mathbb{R}^{2n \times 2n}$ satisfying $\left[\begin{smallmatrix} \tilde{R} & S \\ \star & \tilde{R} \end{smallmatrix}\right] \geq 0$ with $\tilde{R} = \mathrm{diag}\{R, 3R\}$, the following inequality holds

$$-\bar{\eta}\int_{t-\eta_M}^{t-\eta_m} l^T(s)Rl(s)ds \leq 2\wp_1^T S \wp_2 - \wp_1^T \tilde{R}\wp_1 - \wp_2^T \tilde{R}\wp_2 + 2\Im(dw(t)) \quad (24)$$

where

$$\begin{aligned} \wp_1 &:= \nu(t - \eta_M, t - \eta(t)), \quad \wp_2 := \nu(t - \eta(t), t - \eta_m) \\ \Im(dw(t)) &:= \wp_1^T \tilde{R}\beta(t - \eta_M, t - \eta(t)) \\ &\quad + \wp_2^T \tilde{R}\beta(t - \eta(t), t - \eta_M) \end{aligned} \quad (25)$$

where $\nu(\cdot, \cdot)$ and $\beta(\cdot, \cdot)$ are defined in (23).

III. DISSIPATIVE PERFORMANCE ANALYSIS

In this section, by Lyapunov-Krasovskii functional (LKF) method, and based on Lemmas 1 and 2, some sufficient conditions are derived such that the filtering error system (18) is asymptotically stable and dissipative. First, choose the following Lyapunov-Krasovskii functional

$$V(t) = \xi^T(t)P\xi(t) + V_1(t) + V_2(t) \tag{26}$$

where

$$\begin{aligned} V_1(t) :&= \int_{t-d_m}^{t} x^T(s)Q_1x(s)ds + \int_{t-d_M}^{t-d_m} x^T(s)Q_2x(s)ds \\ V_2(t) :&= d_m \int_{t-d_m}^{t}\int_{\theta}^{t} r^T(s)R_1r(s)dsd\theta \\ &\quad + (d_M - d_m)\int_{t-d_M}^{t-d_m}\int_{\theta}^{t} r^T(s)R_2r(s)dsd\theta \end{aligned}$$

where $r(t) = -\tilde{A}x(t) + \tilde{B}\tilde{f}(x(t)) + \tilde{E}v(t)$ and $P > 0$, $Q_1 > 0$, $Q_2 > 0$, $R_1 > 0$, $R_2 > 0$ to be determined.

By Lemmas 1 and 2, we derive the following results.

Proposition 1: For given scalars d_m, d_M and real matrices $\Psi_0 \geq 0$, $\Psi_1 = -\tilde{\Psi}_1^T\tilde{\Psi}_1 \leq 0$, Ψ_2, $\Psi_3 = \tilde{\Psi}_3^T\tilde{\Psi}_3 \geq 0$, the filtering error system (18) is asymptotically stable and dissipative, if there exist real matrices $P = \left[\begin{smallmatrix} P_1 & P_2 \\ \star & P_3 \end{smallmatrix}\right] > 0$, $\Omega > 0$, $Q_i > 0$, R_i $(i = 1, 2)$, real diagonal matrices $\Lambda > 0$ and $S = \left[\begin{smallmatrix} S_{11} & S_{12} \\ S_{21} & S_{22} \end{smallmatrix}\right]$ such that

$$\Omega_1 := \begin{bmatrix} \tilde{R}_2 & S \\ \star & \tilde{R}_2 \end{bmatrix} \geq 0 \tag{27}$$

$$\Omega_2 := \begin{bmatrix} \Sigma_1 & d_m\Gamma_1^TR_1 & (d_M - d_m)\Gamma_1^TR_2 \\ \star & -R_1 & 0 \\ \star & \star & -R_2 \end{bmatrix} < 0 \tag{28}$$

where $\tilde{R}_2 := \mathrm{diag}\{R_2, 3R_2\}$ and

$$\Gamma_1 = \mathrm{col}\{-\tilde{A}^T, 0, 0, 0, 0, \tilde{B}^T, 0, 0, 0, \tilde{E}^T\}$$

and Σ_1 is defined in (31), as shown at the bottom of next page, where

$$\begin{aligned} \vartheta_{11} :&= \mathrm{He}\{-P_1\tilde{A}\} + \lambda\tilde{G} + Q_1 - 4R_1 - C_2^T\Psi_1C_2 \\ \vartheta_{12} :&= P_2A_f - \tilde{A}^TP_2 + C_2^T\Psi_1C_f \\ \vartheta_{22} :&= \mathrm{He}\{P_3A_f\} - C_f^T\Psi_1C_f, \\ \vartheta_{2,10} :&= P_2^T\tilde{E} + C_f^T\Psi_2 \\ \vartheta_{33} :&= Q_2 - Q_1 - 4R_1 - 4R_2, \\ \vartheta_{34} :&= (S_{11} + S_{21} + S_{12} + S_{22})^T - 2R_2, \\ \vartheta_{35} :&= (-S_{11} + S_{21} - S_{12} + S_{22})^T \\ \vartheta_{39} :&= (-2S_{21} - 2S_{22})^T \\ \vartheta_{44} :&= \mathrm{He}\{-S_{11} - S_{21} + S_{12} + S_{22}\} - 4R_2 + \lambda C_1^T\Omega C_1 \\ \vartheta_{45} :&= S_{11}^T - S_{21}^T - S_{12}^T + S_{22}^T - 2R_2 \\ \vartheta_{55} :&= -Q_2 - 4R_2 \\ \vartheta_{48} :&= 6R_2 - 2(S_{12} + S_{22}) \\ \vartheta_{49} :&= 6R_2 + 2(S_{21} - S_{22})^T \\ \vartheta_{55} :&= -Q_2 - 4R_2, \\ \vartheta_{58} :&= 2(S_{12} - S_{22}) \end{aligned}$$

Remark 2: Dissipativity analysis is proposed in the above proposition, where H_∞, passivity and dissipativity could be solved in one framework, if taking some special values of Ψ_1, Ψ_2 and Ψ_3. When $\Psi_1 = I$, $\Psi_2 = 0$ and $\Psi_3 = \gamma^2 I$, the dissipative filtering reduces to the H_∞ filtering problem [18]. If $\Psi_1 = 0$, $\Psi_2 = I$ and $\Psi_3 = \gamma I$, the dissipative filtering becomes the passive filtering issue [23]. Meanwhile, from the proof of Proposition 1, one can see that dissipavity implies stability, therefore, the stability criterion could be easily derived when external disturbance $v(t) = 0$.

Remark 3: Since Lemma 2 is an improvement over Jensen's inequality without using the free-weighting matrix approach, Proposition 1 is less conservative than the ones using the Jensen's inequality and fewer slack variable matrices are introduced to estimate the upper bounds of some related integral terms.

IV. DISSIPATIVE FILTER DESIGN

In this section, dissipative filter will be designed based on Proposition 1.

Proposition 2: For given scalars d_m, d_M and real matrices $\Psi_1 = -\tilde{\Psi}_1^T\tilde{\Psi}_1 \leq 0$, Ψ_2, $\Psi_3 = \tilde{\Psi}_3^T\tilde{\Psi}_3 \geq 0$, the dissipative filter can be designed if there exist real matrices $P_1 > 0$, $Q_1 > 0$, $Q_2 > 0$, $R_1 > 0$, $R_2 > 0$, $W > 0$, $\Omega \geq 0$ and real matrices $S = \left[\begin{smallmatrix} S_{11} & S_{12} \\ S_{21} & S_{22} \end{smallmatrix}\right]$, $\hat{A}_f$, $\hat{B}_f$ and $\hat{C}_f$, such that $P_1 > U$, $\Omega_1 \geq 0$ and

$$\tilde{\Omega}_2 := \begin{bmatrix} \tilde{\Sigma}_1 & d_m\Gamma_1^TR_1 & (d_M - d_m)\Gamma_1^TR_2 & \tilde{\Gamma}_1 \\ \star & -R_1 & 0 & 0 \\ \star & \star & -R_2 & 0 \\ \star & \star & \star & -I \end{bmatrix} < 0 \tag{29}$$

where $\tilde{\Gamma}_1 = \mathrm{col}\{C_2^T\tilde{\Psi}_1^T, \hat{C}_f^T\tilde{\Psi}_1^T, \underbrace{0, \cdots, 0}_{8}\}$, and $\tilde{\Omega}_1 = (\tilde{\vartheta}_{ij})_{10\times 10}$ with $\tilde{\vartheta}_{ij} = \vartheta_{ij}$ $(i, j = 1, 2, \cdots, 17)$ except

$$\begin{aligned} \tilde{\vartheta}_{11} &= \mathrm{He}\{-P_1\tilde{A}\} + Q_1 - 4R_1 + \lambda\tilde{G} \\ \tilde{\vartheta}_{12} &= \hat{A}_f - \tilde{A}^TW^T, \quad \tilde{\vartheta}_{22} = \hat{A}_f + \hat{A}_f^T, \\ \tilde{\vartheta}_{26} &= W\tilde{B}, \quad \tilde{\vartheta}_{2,10} = W\tilde{E} + C_f^T\Psi_2 \end{aligned}$$

and ϑ_{ij} $(i, j = 1, 2, \cdots, 10)$ are defined in Proposition 1.

The parameters of the dissipative filter are given as

$$A_f = \hat{A}_fW^{-1}, \ B_f = \hat{B}_f, \ C_f = \hat{C}_fW^{-1} \tag{30}$$

V. AN ILLUSTRATIVE EXAMPLE

In this section, a numerical example is given to illustrate the proposed method.

Example 1: Consider the GRN (1) with

$$A = \begin{bmatrix} 1.84 & 0 & 0 \\ 0 & 1.32 & 0 \\ 0 & 0 & 1.54 \end{bmatrix}, \quad B = \begin{bmatrix} 0 & 0.8 & -0.8 \\ -0.8 & 0 & 0.8 \\ 0 & -0.8 & 0 \end{bmatrix},$$

$$C = \mathrm{diag}\{1.62, 1.53, 1.21\}, \quad D = \mathrm{diag}\{1.8, 1.5, 1.2\},$$

$$E_m = \mathrm{col}\{0.2, 0.15, 0.1\}, \quad E_p = \mathrm{col}\{0.18, 0.21, 0.25\}.$$

Select $\underline{h} = 0.12s$ and $\bar{h} = 0.18s$. The neuron activation function is given by $f(x) = 0.1\tanh(x)$.

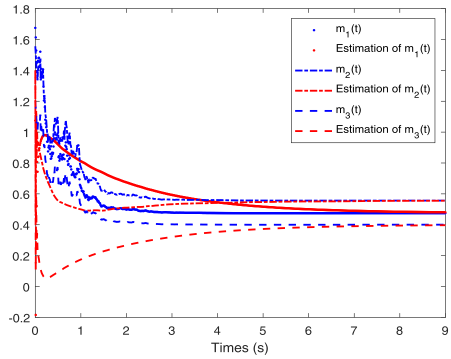

FIGURE 2. mRNA concentrations and their estimates under the H_∞ filter.

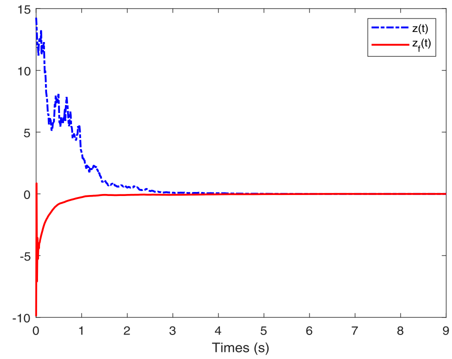

FIGURE 4. $z(t)$ and its estimation $z_f(t)$ under the H_∞ filter.

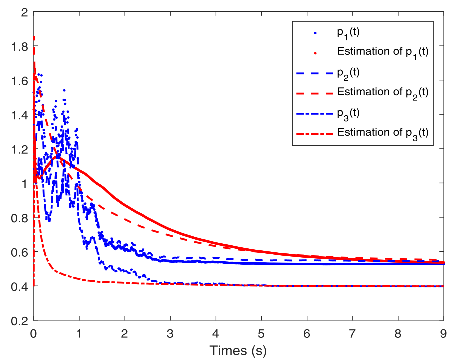

FIGURE 3. Protein concentrations and their estimates under the H_∞ filter.

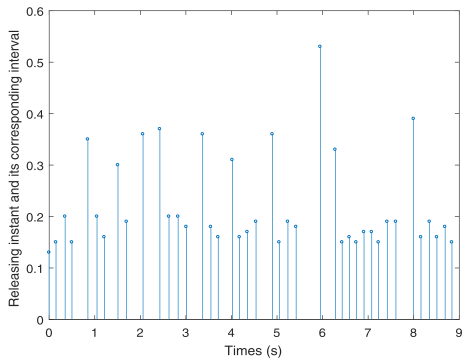

FIGURE 5. Event-triggered releasing instants and releasing interval under the H_∞ filter.

Suppose that the transmission delays belong to [0.12 0.18]. In the following, we will design suitable filters to estimate the states (proteins and the mRNAs) of neurons based on Proposition 2.

- *H_∞ filtering:* Set $\Psi_0 = 0$, $\Psi_1 = -I$, $\Psi_2 = 0$ and $\Psi_3 = 2.7^2\ I$. Applying Proposition 2, the filter parameters A_f, B_f and C_f are given as in next page. The triggering matrix Ω is solved as

$$\Omega = \begin{bmatrix} 0.1557 & 0.0307 \\ 0.0307 & 1.2697 \end{bmatrix}.$$

In the simulation, parameters are chosen the same as in [4]. The equilibrium point of the genetic network is $m^* = [0.4753\ \ 0.5563\ \ 0.4004]^T$ and $p^* = [0.5282\ \ 0.5453\ \ 0.3970]^T$. The initial values of the proteins and their corresponding mRNAs are chosen as $[1.2\ \ 1\ \ 0.8]^T$ and $[1\ \ 0.8\ \ 0.7]^T$. Associated with the obtained H_∞ filter, under the disturbance $v(t) = e^{-t}\sin t$, Fig. 2 and Fig. 3 plot the actual trajectories of the mRNA concentrations $m_i(t)$ and the actual trajectories of protein concentrations $p_i(t)$ with their estimates.

$$\Sigma_1 := \begin{bmatrix}
\vartheta_{11} & \vartheta_{12} & -2R_1 & P_2B_fC_1 & 0 & P_1\tilde{B}+\rho\Lambda & 6R_1 & 0 & 0 & P_1\tilde{E}-C_2^T\Psi_2 & P_2B_f \\
\star & \vartheta_{22} & 0 & P_3B_fC_1 & 0 & P_2^T\tilde{B} & 0 & 0 & 0 & \vartheta_{2,10} & P_3B_f \\
\star & \star & \vartheta_{33} & \vartheta_{34} & \vartheta_{35} & 0 & 6R_1 & 6R_2 & \vartheta_{39} & 0 & 0 \\
\star & \star & \star & \vartheta_{44} & \vartheta_{45} & 0 & 0 & \vartheta_{48} & \vartheta_{49} & 0 & -\lambda C_1^T\Omega \\
\star & \star & \star & \star & \vartheta_{55} & 0 & 0 & \vartheta_{58} & 6R_2 & 0 & 0 \\
\star & \star & \star & \star & \star & -2\Lambda & 0 & 0 & 0 & 0 & 0 \\
\star & \star & \star & \star & \star & \star & -12R_1 & 0 & 0 & 0 & 0 \\
\star & \star & \star & \star & \star & \star & \star & -12R_2 & 4S_{22}^T & 0 & 0 \\
\star & \star & \star & \star & \star & \star & \star & \star & -12R_2 & 0 & 0 \\
\star & \star & \star & \star & \star & \star & \star & \star & \star & -\Psi_3 & 0 \\
\star & \star & \star & \star & \star & \star & \star & \star & \star & \star & -(1-\lambda)\Omega
\end{bmatrix} \tag{31}$$

$$\zeta(t) := \mathrm{col}\{x(t), x_f(t), x(t-d_m), x(t-d(t)), x(t-d_M), \tilde{f}(x(t)), v(t), v_1(t), v_2(t), v_3(t), \psi(t-d(t))\} \tag{32}$$

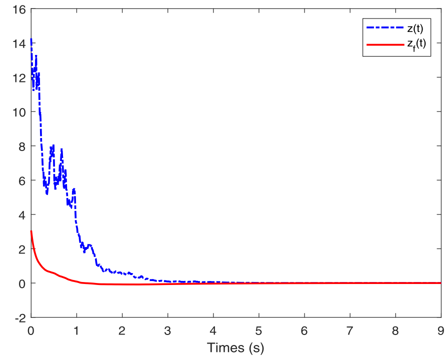

FIGURE 6. ***z*(*t*) and its estimation $z_f(t)$ under the passive filter.**

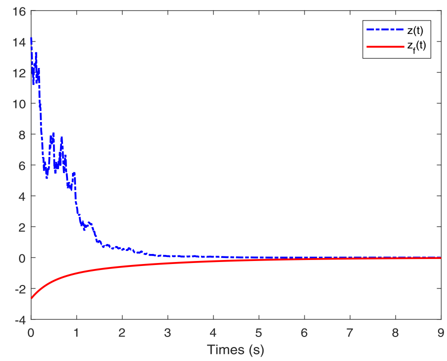

FIGURE 7. ***z*(*t*) and its estimation $z_f(t)$ under the mixed H_∞ and passive filter.**

The output $z(t)$ and its estimation $z_f(t)$ are plotted in Fig. 4. Fig. 5 depicts the event-based release instants and release interval, which reflects that the transmission rate is 78.8% with $\lambda = 0.7$. From this figure, one can see that the H_∞ filter can estimate the $z(t)$ well.

- *Passive filtering:* Let $\Psi_0 = 0$, $\Psi_1 = 0$, $\Psi_2 = I$ and $\Psi_3 = 0.8\,I$. Associated with the passive filter solved by Proposition 2, the signal $z(t)$ and its estimation $z_f(t)$ are depicted in Fig. 6.
- *Mixed H_∞ and passive filtering:* Set $\Psi = 0$, $\Psi_1 = -\gamma^{-1}\alpha I$, $\Psi_2 = (1-\alpha)I$ and $\Psi_3 = \gamma I$ with $\alpha = 0.5$ and $\gamma = 1.8$. With with the mixed H_∞ and passive filter calculated by Proposition 2, Fig. 7 shows the signal $z(t)$ and its estimation $z_f(t)$.
- *(Q, S, R)-dissipative filtering:* Set $\Psi_0 = 0$, $\Psi_1 = -2I$, $\Psi_2 = 2I$ and $\Psi_3 = 2.5\,I$. Under the dissipative filter derived by Proposition 2, the signal $z(t)$ and its estimation $z_f(t)$ are plotted in Fig. 8.

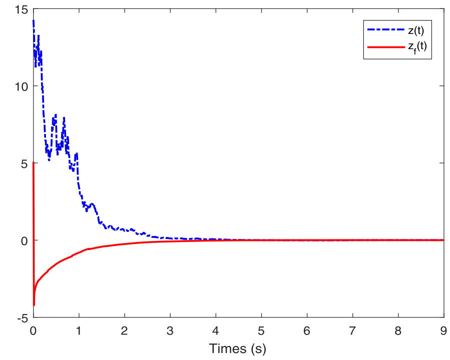

FIGURE 8. ***z*(*t*) and its estimation $z_f(t)$ under the dissipative filter.**

VI. CONCLUSION

In this paper, to tradeoff communication resources and estimation performance of GRNs, a novel event-triggered scheme is proposed to study network-based dissipative filtering for stochastic genetic regulatory networks. In the communication strategy, the event-triggered data generator is proposed to select the necessary data to be transmitted to the filter in an aperiodic sampling way, which can effectively reduce the communication traffic. Under this strategy, the filtering error system has been modeled as a sampled-data error dependent stochastic time-delay system. A linear matrix inequality based approach has been presented to design suitable filters such that some certain filtering performance can be ensured. This designed filtering strategy is more suitable for GRNs in communication network environments with limited load and bandwidth. The effectiveness of the proposed dissipative filtering approach has been demonstrated by a numerical example.

APPENDIXES

Proof of Proposition 1: Using the Itô's formula, the differential of $V(t)$ can be calculated as

$$\mathscr{L}V(t) = 2\xi^T(t)P\bar{r}(t) + \bar{g}^T(t)P\bar{g}(t) + \mathscr{L}V_1(t) + \mathscr{L}V_2(t) \quad (33)$$

where $\bar{r} = \bar{A}\xi(t) + \bar{B}\tilde{f}(x(t)) + \bar{B}_f H\xi(x(t-d(t))) + \bar{E}v(t)$, and

$$\begin{aligned}\mathscr{L}V_1(t) &= x^T(t)Q_1x(t) + x^T(t-d_m)Q_2x(t-d_m)\\ &\quad - x^T(t-d_m)Q_1x(t-d_m)\\ &\quad - x^T(t-d_M)Q_2x(t-d_M)\end{aligned} \quad (34)$$

$$A_f = \begin{bmatrix} -45.4640 & -17.8921 & -48.7770 & -0.0497 & 5.3023 & 11.5301\\ -24.4090 & -53.3619 & -46.5000 & -14.8446 & 13.3665 & 24.8146\\ -30.6461 & 3.5150 & -87.9039 & 4.9067 & -19.4099 & 21.3228\\ 25.6066 & -14.7137 & -8.3357 & -21.5762 & 5.8830 & 11.1914\\ -3.4430 & 34.8490 & -2.8238 & 17.1985 & -21.5074 & -2.5787\\ 23.1138 & -1.9780 & 81.3899 & 2.1234 & 18.0311 & -40.4255 \end{bmatrix}, B_f = \begin{bmatrix} 1.2084 & -3.4228\\ 0.0339 & -0.0371\\ 0.0257 & 0.1044\\ 0.0314 & -0.0748\\ -0.0376 & -0.1629\\ 0.0055 & 0.0197\\ -0.0380 & 0.0911 \end{bmatrix}$$

$$C_f = \begin{bmatrix} -1.9061 & -9.0065 & -1.5035 & -1.6959 & 1.2056 & -1.5005 \end{bmatrix}$$

$$\begin{aligned}\mathscr{L}V_2(t) = {} & d_m^2 r^T(t)R_1 r(t) + (d_M - d_m)^2 r^T(t)R_2 r(t) \\ & -d_m \int_{t-d_m}^{t} r^T(\theta)R_1 r(\theta)d\theta \\ & -(d_M - d_m)\int_{t-d_M}^{t-d_m} r^T(\theta)R_2 r(\theta)d\theta \end{aligned} \tag{35}$$

By Lemma 1, we have

$$-d_m \int_{t-d_m}^{t} r^T(t)R_1 r(s)ds \le 2\psi_{01}^T \tilde{R}_1 \psi_{01} + 2\psi_{01}^T \tilde{R}_1 \nu_{01} \tag{36}$$

where $\tilde{R}_1 := \mathrm{diag}\{R_1, 3R_1\}$; and

$$\begin{cases} \psi_{01}(t) := \begin{bmatrix} x(t) - x(t-d_m) \\ x(t) + x(t-d_m) - \frac{2}{d_m}\int_{t-d_m}^{t} x(\theta)d\theta \end{bmatrix} \\ \nu_{01}(t) := \begin{bmatrix} \int_{t-d_m}^{t} g(\theta)d\theta \\ \int_{t-d_m}^{t}(d_m + 2\theta)g(\theta)d\theta \end{bmatrix} \end{cases}$$

Apply Lemma 2 to obtain

$$\begin{aligned} -(d_M - d_m)\int_{t-d_M}^{t-d_m} & r^T(\theta)\tilde{R}_2 r(\theta)d\theta \\ \le {} & 2\psi_{11}^T S\psi_{21} - \psi_{11}^T \tilde{R}_2 \psi_{11} - \psi_{21}^T \tilde{R}_2 \psi_{21} \\ & +2\psi_{11}^T \tilde{R}_3 \phi_1 + 2\psi_{21}^T \tilde{R}_3 \phi_2 \end{aligned} \tag{37}$$

where $\tilde{R}_2 := \mathrm{diag}\{R_2, 3R_2\}$, $\tilde{R}_3 := \mathrm{diag}\{R_2, R_2\}$ and

$$\begin{cases} \psi_{11} := \begin{bmatrix} x(t-d(t)) - x(t-d_M) \\ x(t-d(t)) + x(t-d_M) - 2v_3(t) \end{bmatrix} \\ \psi_{21} := \begin{bmatrix} x(t-d_m) - x(t-d(t)) \\ x(t-d_m) + x(t-d(t)) - 2v_2(t) \end{bmatrix} \end{cases}$$

with

$$\begin{cases} v_2(t) := \frac{1}{d(t)-d_m}\int_{t-d(t)}^{t-d_m} x(s)ds \\ v_3(t) := \frac{1}{d_M-d(t)}\int_{t-d_M}^{t-d(t)} x(s)ds \end{cases}$$

$$\begin{cases} \phi_1 := \begin{bmatrix} \int_{x}^{x(t-d(t))}(t-d_M)g(s)dw(s) \\ \dfrac{1}{d_M - d(t)}\int_{x(t-d_M)}^{x(t-d(t))}(d_M - d(t) + 2s)g(s)dw(s) \end{bmatrix} \\ \phi_2 := \begin{bmatrix} \int_{x(t-d(t))}^{x}(t-d_m)g(s)dw(s) \\ \dfrac{1}{d(t) - d_m}\int_{x(t-d(t))}^{x(t-d_m)}(d(t) - d_m + 2s)g(s)dw(s) \end{bmatrix} \end{cases}$$

Substituting (36)-(37) into (33) yields

$$\mathscr{L}V(t) - J(t) \le \zeta^T(t)\Upsilon\zeta(t) \tag{38}$$

where $\zeta(t)$ is defined in [(32), p. 6], and

$$\Upsilon := \Omega + \Gamma_1\left[d_m^2 R_1 + (d_M - d_m)^2 R_2\right]\Gamma_1^T$$

If the matrix inequality in (28) is satisfied, applying the Schur complement yields $\Upsilon < 0$. Thus, there exists a scalar $\sigma > 0$ such that

$$\mathscr{L}V(t) - J(t) \le -\sigma\zeta^T(t)\zeta(t) \le 0 \tag{39}$$

Then, under zero-initial condition, the filtering error system (18) is dissipative.

Next, we prove that when $v(t) \equiv 0$, the filtering error system (18) is asymptotically stable if the matrix inequalities in (27) and (28) are satisfied. First, set $v(t) \equiv 0$. Then from (20) and (39), with $\Psi_1 \le 0$, we have

$$\begin{aligned}\dot{V}(t) & \le e^T\Psi_1 e(t) - \sigma\xi^T(t)\xi(t) \\ & \le -\sigma\xi^T(t)\xi(t) < 0, \quad \text{for } \xi(t) \ne 0 \end{aligned} \tag{40}$$

Therefore, the filtering error system (18) with $v(t) \equiv 0$ is asymptotically stable, which completes the proof. □

Proof of Proposition 2 is similar to the proof of Proposition 11 in [24], so the proof is omitted.

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