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Quantized Control Design for Cognitive Radio Networks Modeled as Nonlinear Semi-Markovian Jump Systems

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Abstract—This paper is concerned with the quantized control design problem for a class of semi-Markovian jump systems with repeated scalar nonlinearities. A semi-Markovian system of this kind has been transformed into an associated Markovian system via a supplementary variable technique and a plant transformation. A sufficient condition for associated Markovian jump systems is developed. This condition guarantees that the corresponding closed-loop systems are stochastically stable and have a prescribed $H_{\infty}$ performance. The existence conditions for full- and reduced-order dynamic output feedback controllers are proposed, and the cone complementarity linearization procedure is employed to cast the controller design problem into a sequential minimization one, which can be solved efficiently with existing optimization techniques. Finally, an application to cognitive-radio systems demonstrates the efficiency of the new design method developed.

Index Terms—Cognitive radio (CR) network, output feedback control, quantization, repeated scalar nonlinearity, semi-Markovian jump systems (S-MJSs).

I. INTRODUCTION

As a special class of stochastic dynamic systems, Markovian jump systems (MJSs) have attracted extensive research attention over the past years due to their practical applications in manufacturing, power, aerospace, and networked control systems. Over the last decades, a great deal of effort has been devoted to the analysis and synthesis of MJS. For some representative works on this general topic, we refer to [15], [16], [24], [26], [27], [31], and the references therein. However, MJSs have many limitations in applications since the jump time of a Markov chain is, in general, exponentially distributed, and the results obtained for the MJS are intrinsically conservative due to constant transition rates.

Different from the MJS, semi-Markovian jump systems (S-MJSs) are characterized by a fixed matrix of transition probabilities and a matrix of sojourn time probability density functions. Due to their relaxed conditions on the probability distributions, S-MJSs have much broader applications than the conventional MJS. Indeed, most of the modeling, analysis, and design results for MJS would be special cases of S-MJS. Thus, this area of research is significant not only in theory but also in practice. However, the main obstacle to investigate S-MJS is the problem of how to transform a denumerable-phase semi-Markov process into a Markov chain. The stochastic stability of linear systems with phase-type semi-Markovian jump parameters is studied in [14]. Inspired by the fact that a transition rate in S-MJS is time varying instead of a constant one in MJS, probability distributions of sojourn time for semi-Markovian processes, from an exponential distribution to a Weibull one, are discussed in [13]. In the aforementioned works, the system states are assumed to be available. In practice, the system states are often difficult and/or expensive to measure or even not available due to the factors of cost, technique, etc. [2], [3], [11], [18], [19], [30]. Therefore, the output feedback controller design for the systems with unmeasured states is a challenging issue in the synthesis of S-MJS.

During the past decades, with the growing interest in networked control systems, the problem of stabilizing plants over saturating quantized measurements has attracted increasing attention from the research community. In the network environment, the system outputs are always required to be quantized before transmission. In other words, real-valued signals are mapped into piecewise-constant signals taking values in finite sets, which are employed when the observation and control signals are sent via constrained communication channels. More importantly, new quantization techniques are needed for the sensor measurements and control commands that are sent over networks. Some efforts have been made toward this line; see, e.g., [10] and [17]. In fact, modern control theory has been the focus of significant research subjects in networks, remote control technology, and communication.

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controller can guarantee that the corresponding closed-loop systems are stochastically stable and have a prescribed $H_{\infty}$ performance; 4) a sufficient condition for the existence of admissible controllers in terms of matrix equalities is established, and a cone complementarity linearization (CCL) procedure is employed to transform a nonconvex feasibility problem into a sequential minimization problem, which can be readily solved by existing optimization techniques; and 5) full- and reduced-order DOFCs to handle the case of unmeasured states are designed.

The rest of this paper is organized as follows. In Section II, the Markovization and quantized $H_{\infty}$ output controller design problems are formulated, and our main results are presented in Section III. CR systems are provided in Section IV to demonstrate the effectiveness and potential of proposed new design techniques. Finally, this paper is concluded in Section V.

Notation: Throughout this paper, $\mathbb{R}^n$ denotes the $n$-dimensional Euclidean space, $\mathbb{R}^{m \times n}$ is the space of real matrices of dimension $m \times n$, and the notation $P > 0$ means that $P$ is real symmetric and positive definite. $I$ and $0$ represent the identity matrix and zero matrix, respectively, and $I_k \triangleq \begin{bmatrix} 1 & \ldots & 1 \end{bmatrix}^T \in \mathbb{R}^k$. $\otimes$ denotes the Kronecker product of matrices. diag{·} stands for a block-diagonal matrix. $E\{\cdot\}$ denotes the expectation operator. $\ell_2[0, \infty)$ refers to the space of square-summable infinite vector sequences over $[0, \infty)$. The notation $(\Omega, \mathcal{F}, \Pr)$ represents the probability space with the sample space $\Omega$, $\sigma$-algebra $\mathcal{F}$ of subsets of the sample space, and probability measure $\Pr$. $|\cdot|$ refers to the Euclidean vector norm. For a matrix $U \in \mathbb{R}^{m \times n}$ with rank $k$, we denote its orthogonal complement as $U^\perp$, which is defined as a (possibly nonunique) $(m-k) \times m$ matrix with rank $m - k$ such that $U^\perp U = 0$. $\|\cdot\|_2$ stands for the conventional $\ell_2[0, \infty)$ norm. $\operatorname{tr}(\cdot)$ refers to the trace. $\lambda_{\min}(\cdot)$ is used for the minimum eigenvalues of a symmetric matrix. In symmetric block matrices or long matrix expressions, we use * to represent a term that is induced by symmetry.

II. PROBLEM FORMULATION

In this section, a new channel model, called finite-state phase-type (PH) semi-Markov channel model, is proposed. It is an extension of the traditional Markov channel model by introducing PH distributed sojourn time at each state. We first introduce a rigorous mathematical definition for the PH semi-Markov process.

Definition 1: Phase-type distribution is the distribution of time to absorption in an absorbing Markov process with some transient states and one absorbing state.

Assumption 1: Assume that the absorbing state is reached with probability one for a finite time. Define an absorbing Markov chain $\{\bar{r}_k, k \geq 0\}$ on the state space $\{1, 2, \ldots, m + 1\}$, where the states $1, 2, \ldots, m$ are transient and the state $m + 1$ is absorbing. The infinitesimal generator of $\bar{r}_k$ is given by $Q = \begin{bmatrix} T & T_0 \\ 0_{1 \times m} & 1 \end{bmatrix}$, where the matrix $T = (T_{ij})_{m \times m}$ satisfies $T_{ij} \geq 0$, $T e \preceq e$, where $e$ denotes an appropriately dimensioned column vector with all components equal to one. $T^0 = (I - T)e$ is a column vector, and $I - T$ is...
nonsingular. The initial probability distribution of this chain is denoted by \((a_i, a_{m+1})\), where \(a\) is a row vector with dimension \(m\). We then have \(aa + a_{m+1} = 1\). In PH distribution, \(m\) is called the order of the distribution, and the states of the absorbing Markov process are called phases. The PH distribution can be fully represented by \((a, T)\).

**Definition 2—[21]:** Let \(E\) be a finite or countable set. A stochastic process \(\bar{r}_k\) on the state space \(E\) is called a denumerable PH semi-Markov process if the following conditions hold.

1. The sample paths of \((\bar{r}_k, k < +\infty)\) are right-continuous functions and have left-hand limits with probability one.
2. Denote the \(n\)th jump point of the process \(\bar{r}_k\) by \(\tau_n\), where \(\tau_0 = 0 < \tau_1 < \tau_2 < \cdots < \tau_n < \cdots\), and \(\tau_n, n = 1, 2, \ldots\), are Markovian moments of the process \(\bar{r}_k\).
3. \(F_{ij}(k) \triangleq \Pr\{\tau_{n+1} - \tau_n \leq k | \bar{r}_{\tau_n} = i, \bar{r}_{\tau_{n+1}} = j\} = F_i(k), i, j \in E, k \geq 0,\) do not depend on \(j\) and \(n\).
4. \(F_i(k), i \in E,\) is a phase-type distribution.

We consider the following stochastic systems governed by a PH semi-Markov process in the probability space \((\Omega,F,Pr)\) for \(k > 0\)

\[
\begin{align*}
x(k+1) &= \bar{A}(\bar{r}_k)g(x(k)) + \bar{B}(\bar{r}_k)u(k) + \bar{F}(\bar{r}_k)\omega(k) \\
y(k) &= \bar{C}(\bar{r}_k)g(x(k)) + D(\bar{r}_k)\omega(k) \\
z(k) &= \bar{E}(\bar{r}_k)g(x(k))
\end{align*}
\]

where \(x(k) \in \Re^n\) represents the state vector, \(y(k) \in \Re^p\) is the measured output, \(z(k) \in \Re^m\) is the control output, \(u(k) \in \Re^m\) is the control input, \(\omega(k) \in \Re^r\) is the exogenous disturbance input which belongs to \(\ell_2[0, \infty)\), and \(\bar{A}(\bar{r}_k), \bar{B}(\bar{r}_k), \bar{C}(\bar{r}_k), \bar{D}(\bar{r}_k), \bar{E}(\bar{r}_k),\) and \(\bar{F}(\bar{r}_k)\) are matrix functions of the PH semi-Markov process \(\{\bar{r}_k, k \geq 0\}\).

**Remark 1:** In our study, we consider a set of stochastic systems with modal transition given by a phase-type semi-Markov chain but not with arbitrarily switching. More specifically, the times between transitions are phase-type random variables. It is worth noting that the phase-type distribution is a generalization of the exponential distribution while still preserving much of its analytic tractability and has been used in a wide range of stochastic modeling applications in areas as diverse as reliability theory, queuing theory, and biostatistics.

In what follows, we recall some definitions and lemmas, which will be used in the development of our main results in the sequel. Then, a new supplementary variable technique and a plant transformation are presented, by which a semi-Markovian system has been transformed into an associated Markovian system.

Let \((a^{(i)}, T^{(i)}), i \in E,\) denote the \(m^{(i)}\) order representation of \(F_i(k)\) and \(E^{(i)}\) be the corresponding set of all transient states, where

\[
\begin{align*}
F_i(k) &\triangleq \Pr\{\tau_{n+1} - \tau_n \leq k | \bar{r}_{\tau_n} = i\}, \quad i \in E \\
(a^{(i)}) &\triangleq (a_1^{(i)}, a_2^{(i)}, \ldots, a_{m^{(i)}}^{(i)}) \\
(T^{(i)}) &\triangleq (T_{vs}^{(i)}), \quad v, s \in E^{(i)}.
\end{align*}
\]

It can be shown that the number of the elements in \(E^{(i)}\) is \(m^{(i)}\). Also, let

\[
\begin{align*}
p_{ij} &\triangleq \Pr\{\bar{r}_{n+1} = j | \bar{r}_n = i, i, j \in E\} \\
P &\triangleq (p_{ij}, i, j \in E) \\
(a, T) &\triangleq \left\{ \left( a^{(i)}, T^{(i)} \right), i \in E \right\}.
\end{align*}
\]

Obviously, the probability distribution of \(\bar{r}_k\) can be determined only by \(\{P, (a, T)\}\). For every \(n, \tau_n \leq k \leq \tau_{n+1}\), define

\[
J(k) \triangleq \text{the phase of } F_{\bar{r}_k}(\cdot) \text{ at time } k - \tau_n.
\]

For any \(i \in E,\) define

\[
T_j^{(i,0)} \triangleq - \sum_{s=1}^{m^{(i)}} T_{js}^{(i)}, \quad j = 1, 2, \ldots, m^{(i)}
\]

\[
G \triangleq \left\{ (i, s^{(i)}) | i \in E, s^{(i)} = 1, 2, \ldots, m^{(i)} \right\}.
\]

**Lemma 1—[14]:** \(Z(k) = (\bar{r}_k, J(k))\) is a Markov chain with state space \(G\) (\(G\) is finite if and only if \(E\) is finite). The infinitesimal generator of \(Z(k)\), given by \(Q = (q_{jk}, \mu, \zeta \in G)\), is determined only by the pair of \((\bar{r}_k, J(k))\) given by \(\{P, (a, T)\}\) as follows:

\[
\begin{align*}
q_{i, (k, l)}^{(i)}(i, k^{(i)}), &\ triangleq_{i, (k, l)}^{(i)} = T_{k^{(i)}}^{(i)} A_{k^{(i)}}, \quad (i, k^{(i)}) \in G \\
q_{i, (k, l)}^{(i)}(i, k^{(i)}), &\ triangleq_{i, (k, l)}^{(i)} = T_{k^{(i)}}^{(i)} A_{k^{(i)}}, \quad (i, k^{(i)}) \in G
\end{align*}
\]

\[
T_{js}^{(i)} = p_{ij} T_{k^{(i)}}^{(i)} A_{k^{(i)}}, \quad i \neq j, (i, k^{(i)}) \in G, \quad (j, k^{(i)}) \in G.
\]

By (3), we obtain that \(G\) has \(N = \sum_{i \in E} m^{(i)}\) elements, so the state space of \(Z(k)\) has \(N\) elements. For convenience, we denote the summation \(\sum_{i=1}^{e} m^{(i)} + s, 1 \leq s \leq m^{(i)}\), by \(\psi(i, s)\); hence,

\[
\psi(i, s) = \sum_{r=1}^{i-1} m^{(r)} + s, \quad i \in E, \quad 1 \leq s \leq m^{(i)}.
\]

Moreover, define

\[
\lambda_{\psi(i, s)\psi(j, s')} \triangleq \psi(Z(k)) = \psi(Z(k))
\]

Therefore, \(r_k\) is an associated Markov process of \(\bar{r}_k\) with the state space \(N = \{1, 2, \ldots, N\}\) and the infinitesimal generator \(\Pi = (\pi_{ij})\), \(1 \leq i, j \leq N\), such that

\[
\pi_{ij} = \Pr\{r_{k+h} = j | r_k = i\}
\]

\[
= \Pr\{\psi(Z(k) + h) = j | \psi(Z(k)) = i\}
\]

where \(\pi_{ij}\) is the transition rate from mode \(i\) at time \(k\) to mode \(j\) at time \(k + h\) when \(i \neq j\) and \(\sum_{j=1}^{N} \pi_{ij} = 1\) for every \(i \in N\).
Then, we can construct the associated Markovian systems, which are equivalent to (1), as follows:
\[
\begin{align*}
  x(k+1) &= A_i g(x(k)) + B_i u(k) + F_i \omega(k) \\
  y(k) &= C_i g(x(k)) + D_i \omega(k) \\
  z(k) &= E_i g(x(k))
\end{align*}
\]
where matrices \( A_i \triangleq A(r_k = i) \), \( B_i \triangleq B(r_k = i) \), \( C_i \triangleq C(r_k = i) \), \( D_i \triangleq D(r_k = i) \), \( E_i \triangleq E(r_k = i) \), and \( F_i \triangleq F(r_k = i) \) are known real constant matrices of appropriate dimensions. The function \( g(\cdot) \) is a nonlinear function satisfying the following assumption as in [4].

**Assumption 2:** The nonlinear function \( g(\cdot) : \mathbb{R} \to \mathbb{R} \) is assumed to satisfy
\[
\forall x, y \in \mathbb{R}, \quad |g(x) + g(y)| \leq |x + y|.
\]
In the sequel, for the vector
\[
x(k) = [x_1(k) \ x_2(k) \ldots x_n(k)]^T
\]
we denote
\[
g(x) \triangleq [g(x_1(k)) \ g(x_2(k)) \ldots g(x_n(k))]^T.
\]
Before entering the controller, the signal \( y(k) \) is quantized by the quantizer \( q_i(\cdot) \) described by
\[
q_i(\cdot) \triangleq \begin{bmatrix} q_i^{(1)}(\cdot) \ q_i^{(2)}(\cdot) \ldots q_i^{(p)}(\cdot) \end{bmatrix}^T, \quad i \in \mathcal{N}
\]
where \( q_i^{(j)}(\cdot) \) is assumed to be symmetric, i.e.,
\[
q_i^{(j)}(y_j(k)) = -q_i^{(j)}(-y_j(k)), \quad j = 1, \ldots, p.
\]
For any \( i \in \mathcal{N} \), the sets of quantized levels are described by
\[
\mathcal{Y}_j \triangleq \left\{ \pm \eta_j^{(i,j)} \eta_j^{(i,j)} \right\} = \left\{ \rho^{(i,j)} \cdot \eta_j^{(i,j)}, \ l = \pm 1, \pm 2, \ldots \right\}
\]
where \( \rho^{(i,j)} \) represents the \( j \)th quantizer density of the subquantizer \( q_i^{(j)}(\cdot) \) and \( \eta_j^{(i,j)} \) denotes the initial values for subquantizer \( q_i(\cdot) \). The associated quantizer \( q_i^{(j)}(\cdot) \) is defined as follows:
\[
q_i^{(j)}(y_j(k)) = \begin{cases} \eta_j^{(i,j)}, & \text{if } \eta_j^{(i,j)} y_j(k) \leq \eta_j^{(i,j)} (1 - \rho^{(i,j)}) \\ -q_j^{(i,j)}(y_j(k)), & \text{if } y_j(k) < 0 \end{cases}
\]
where \( \delta^{(i,j)} = (1 - \rho^{(i,j)}) / (1 + \rho^{(i,j)}) \).

Define \( \Delta_i \), for all \( i \in \mathcal{N} \) as \( \Delta_i \triangleq \text{diag}\{\delta^{(i,1)}, \ldots, \delta^{(i,p)}\} \). It is obvious that \( 0 < \Delta_i < I_p \). From (6), it is not difficult to verify that the logarithmic quantizer can be characterized as follows:
\[
(1 - \delta^{(i,j)}) y_j^2(k) \leq q_i^{(j)}(y_j(k)) y_j(k) \leq (1 + \delta^{(i,j)}) y_j^2(k).
\]
Note that (7) is equivalent to
\[
[q_i(y(k)) - (I_p - \Delta_i) y(k)]^T [q_i(y(k)) - (I_p + \Delta_i) y(k)] \leq 0.
\]
Thus, \( q_i(\cdot) \) can be decomposed as follows:
\[
q_i(y(k)) = (I_p - \Delta_i) \cdot y(k) + q_i^* \cdot y(k)
\]
where \( q_i^* : \mathbb{R}^p \to \mathbb{R}^p \) satisfies \( q_i^*(\cdot) = 0 \), and
\[
(q_i^*(y(k)))^T \cdot [q_i^*(y(k)) - 2 \cdot \Delta_i \cdot y(k)] \leq 0.
\]
For convenience, let
\[
\mathcal{K}_{1i} \triangleq I_p - \Delta_i, \quad \mathcal{K}_{2i} \triangleq I_p + \Delta_i, \quad \mathcal{K}_i \triangleq \mathcal{K}_{2i} - \mathcal{K}_{1i} = 2 \Delta_i.
\]
Therefore, (8) can be written as
\[
q_i^*(y(k))^T \cdot [q_i^*(y(k)) - \mathcal{K}_i \cdot y(k)] \leq 0.
\]
In the following, it is assumed that the output data are quantized before being transmitted to another node in the network. Thus, we get the following associated Markovian jump system:
\[
\begin{align*}
  x(k+1) &= A_i g(x(k)) + B_i u(k) + F_i \omega(k) \\
  y_i(k) &= q_i C_i g(x(k)) + D_i \omega(k) \\
  z(k) &= E_i g(x(k))
\end{align*}
\]
For system (10), we are interested in designing a nonlinear DOFC of the following form:
\[
\begin{align*}
  \dot{x}(k+1) &= \hat{A}_i g(\hat{x}(k)) + \hat{B}_i y_i(k) \\
  \dot{u}(k) &= \hat{C}_i g(\hat{x}(k)) + \hat{D}_i q_i^*(y(k))
\end{align*}
\]
where \( \hat{x}(k) \in \mathbb{R}^n \) is the state vector of the DOFC. The matrices \( \hat{A}_i, \hat{B}_i, \hat{C}_i, \text{ and } \hat{D}_i \) are the controller parameters to be designed.

Augmenting system (10) to include the states of system (11), the closed-loop system is governed by
\[
\begin{align*}
  \dot{\xi}(k+1) &= \hat{A}_i g(\hat{\xi}(k)) + \hat{B}_i \omega(k) + \hat{D}_i q_i^*(y(k)) \\
  \dot{z}(k) &= \hat{C}_i g(\hat{\xi}(k))
\end{align*}
\]
where \( \hat{\xi}(k) \triangleq [x^T(k) \ \hat{x}^T(k)]^T \) and
\[
\hat{A}_i \triangleq \begin{bmatrix} A_i + B_i \hat{D}_i K_i C_i & B_i \hat{C}_i \\ B_i K_i C_i & \hat{A}_i \end{bmatrix}, \quad \hat{C}_i \triangleq [E_i \ 0] \\
\hat{B}_i \triangleq \begin{bmatrix} F_i + B_i \hat{D}_i K_i \hat{D}_i \hat{D}_i \hat{D}_i & B_i \hat{D}_i \\ B_i K_i \hat{D}_i & \hat{B}_i \hat{B}_i \end{bmatrix}, \quad \hat{D}_i \triangleq \begin{bmatrix} B_i \hat{D}_i \\ B_i \hat{D}_i \hat{D}_i \hat{D}_i \hat{D}_i \end{bmatrix}.
\]

**Definition 3**—[27]: The closed-loop system (12) with \( \omega(k) = 0 \) is said to be stochastically stable if the following condition holds for any initial condition \( \xi_0 \in \mathbb{R}^n \) and \( r_0 \in \mathcal{N} \):
\[
\lim_{T \to \infty} \mathbb{E} \left[ \sum_{k=0}^{T} \xi^T(k) \xi(k) \right] \leq M(\xi_0, r_0).
\]

**Definition 4**—[31]: For a given scalar \( \gamma > 0 \), system (12) is said to be stochastically stable with an \( H_\infty \) performance \( \gamma \), if
it is stochastically stable with $\omega(t) = 0$, and under zero initial condition, the following condition holds for all nonzero $\omega(t) \in l_2[0, \infty)$:

$$\mathbb{E} \left\{ \sum_{k=0}^{\infty} z^T(k)z(k) \right\} < \gamma^2 \sum_{k=0}^{\infty} \omega^T(k)\omega(k).$$

**Definition 5—[4]:** A square matrix $P \triangleq [p_{ij}] \in \mathbb{R}^{n \times n}$ is said to be positive diagonally dominant if $P > 0$ (positive definite) and (row) diagonally dominant, i.e.,

$$\forall i,\ p_{ii} \geq \sum_{j \neq i} |p_{ij}|.$$

**Lemma 2—[4]:** Supposing that a matrix $P \succeq 0$ is diagonally dominant, then, for all nonlinear functions $g(\cdot)$ satisfying (4), it holds that

$$\forall x \in \mathbb{R}^n,\ g^T(x)Pgx(x) \leq x^TPx.$$

**Lemma 3—[4]:** A matrix $P$ is positive diagonally dominant if and only if $P > 0$ and there exists a symmetric matrix $R$ such that

$$\forall i \neq j,\ r_{ij} \geq 0,\ p_{ij} + r_{ij} \geq 0$$

$$\forall i,\ p_{ii} \geq \sum_{j \neq i} (p_{ij} + 2r_{ij})$$

which involves only $n(n - 1)/2$ variables $r_{ij}$ in addition to $p_{ij}$ and $n^2$ inequalities in addition to $P > 0$.

**Lemma 4—[9]:** Given a symmetric matrix $W \in \mathbb{R}^{n \times n}$ and two matrices $\mathcal{U}$ and $\mathcal{V}$ of column dimension $m$, consider the problem of finding a matrix $\mathcal{G}$ of compatible dimensions such that

$$W + \mathcal{U}G\mathcal{V} + (\mathcal{V}G\mathcal{V})^T < 0.$$ 

The aforementioned inequality is solvable for $\mathcal{G}$ if and only if

$$\mathcal{U}^TW(\mathcal{U}^T) < 0,\ \mathcal{V}^TW(\mathcal{V}^T) < 0.$$

In this paper, the quantized $H_\infty$ DOFC design problem to be solved can be expressed as follows.

Quantized $H_\infty$ DOFC Design Problem: Given a PH S-MJS (10) with repeated scalar nonlinearities, develop a mode-dependent quantized DOFC (11) such that, for all admissible $\omega(k) \in l_2[0, \infty)$, the closed-loop system (12) is stochastically stable with an $H_\infty$ disturbance attenuation level $\gamma$.

III. MAIN RESULTS

We first investigate the stochastic stability with an $H_\infty$ disturbance attenuation level $\gamma$ of the closed-loop system (12).

**Theorem 1:** Consider the associated Markov jump nonlinear system (10), and suppose that the controller gains $(\hat{A}_i, \hat{B}_i, \hat{C}_i, \hat{D}_i)$ of system (11) are given. Then, the closed-loop system (12) is stochastically stable with an $H_\infty$ disturbance attenuation level $\gamma$ if there exists a set of positive diagonally dominant matrices $P_i$ such that

$$\begin{bmatrix}
-\hat{G}_i^{-1} & 0 & \hat{G}_i & \hat{G}_i \\
* & -I & \hat{C}_i & 0 \\
* & * & -P_i & \Phi_i^T K_i \\
* & * & * & -2I
\end{bmatrix} < 0, \ \forall i \in \mathcal{N}$$

where

$$\hat{G}_i \triangleq \text{diag} \{ \pi_{1i}, \pi_{2i}, \ldots, \pi_{Ni} P_N \}, \ \Phi_i \triangleq [C_i \ 0]$$

$$\hat{G}_i \triangleq [\hat{A}_i^T \hat{A}_i^T \ldots \hat{A}_i^T]^T, \ \hat{G}_i \triangleq [\hat{B}_i^T \hat{B}_i^T \ldots \hat{B}_i^T]^T$$

$$\hat{G}_i \triangleq [\hat{D}_i^T \hat{D}_i^T \ldots \hat{D}_i^T]^T.$$ 

Proof: By the Schur complement, (14) is equivalent to

$$\begin{bmatrix}
-P_i + \hat{C}_i^T \hat{C}_i & \Phi_i^T K_i & 0 & \hat{G}_i \\
* & -2I & \hat{C}_i D_i & \hat{G}_i \\
* & * & -\gamma^2 I & \hat{G}_i \\
-\hat{G}_i & \hat{G}_i & \hat{G}_i & \hat{G}_i
\end{bmatrix} < 0.$$ 

(15)

Let $\hat{P}_i \triangleq \sum_{j=1}^{N} \pi_{ij} P_j$, and then, (15) yields

$$\Psi_i \triangleq \begin{bmatrix}
\Psi_{ii} & \hat{A}_i^T \hat{P}_i \hat{A}_i & + \Phi_i^T K_i \\
* & \hat{D}_i^T \hat{P}_i \hat{D}_i & -2I \\
* & * & -\gamma^2 I + B_i^T \hat{P}_i B_i
\end{bmatrix} < 0.$$ 

(16)

where $\Psi_{ii} \triangleq \hat{A}_i^T \hat{P}_i \hat{A}_i - P_i + \hat{C}_i^T \hat{C}_i$.

First, we demonstrate the stability of the closed-loop system (12) with $\omega(k) = 0$. The inequality (16) implies that

$$\Theta_i \triangleq \begin{bmatrix}
\hat{A}_i^T \hat{P}_i \hat{A}_i & -P_i & \hat{A}_i^T \hat{P}_i \hat{D}_i & + \Phi_i^T K_i \\
* & \hat{D}_i^T \hat{P}_i \hat{D}_i & -2I
\end{bmatrix} < 0.$$ 

Therefore, considering (12) with $\omega(k) = 0$, we obtain

$$\mathbb{E} \{ V_{r_{k+1}} (\xi(k+1), k+1) \mid (\xi(k), r_k = i) \} - V_{r_k} (\xi(k), k)$$

$$\leq \tilde{\xi}^T(k) \Theta_i \tilde{\xi}(k)$$

$$\leq -\lambda_{\min} (\Theta_i) \tilde{\xi}^T(k) \tilde{\xi}(k)$$

$$\leq -\beta \xi^T(k) \xi(k),$$

where $V_{r_k} (\xi(k), k) \triangleq \xi^T(k) P(\xi(k)) \xi(k)$, $\beta \triangleq \inf_{i \in \mathcal{S}} \{ \lambda_{\min} (\Theta_i) \}$, and $\tilde{\xi}(k) \triangleq \left[ \xi^T(k) \left( \xi_{i}^{(r)}(y(k)) \right) \right]^T$. Then, for any $T > 0$

$$\mathbb{E} \{ V_{r_{T+1}} (\xi(T+1), T+1) \mid (\xi(T), r_T) \} - V_{r_0} (\xi(0), 0)$$

$$\leq -\beta \sum_{k=0}^{T} \mathbb{E} \{ \xi^T(k) \xi(k) \}.$$
Consequently,
\[
\sum_{k=0}^{T} E\{\xi^T(k)|\xi(k)\} \leq \frac{1}{\beta} \left( E\{V_{r_0}(\xi(0), 0)\} - E\{V_{r_{T+1}}(\xi(T+1), T+1)|\xi(T), r_T\}\right) \\
\leq \frac{1}{\beta} E\{V_{r_0}(\xi(0), 0)\}.
\]
Hence, it follows that
\[
\lim_{T \to \infty} E\left\{\sum_{k=0}^{T} \xi^T(k)|\xi(0), r_0\right\} \leq M(\xi_0, r_0)
\]
where $M(\xi_0, r_0)$ is a positive number. Note that, by applying Assumption 1, we obtain that the state trajectories of the closed-loop system arrive in the same subsystem within a finite time. Thus, the closed-loop system (12) is stochastically stable in the sense of Definition 3.

Next, we show that the $H_\infty$ performance in the sense of Definition 4 is assured under zero initial condition. Choose a stochastic global Lyapunov function candidate as
\[
V_{r_k}(\xi(k), k) \triangleq \xi^T(k)P(r_k)\xi(k)
\]
where $P_i \triangleq P(r_k = i)$, for $i \in N$, and $P_i$ are the positive diagonally dominant matrices to be determined.

Also, consider the following index:
\[
\mathcal{J}_T^2 \triangleq \sum_{k=0}^{T} E\left\{z^T(k)z(k) - \gamma^2 \omega^T(k)\omega(k)\right\}.
\]
Therefore, under zero initial condition, i.e., $V_{r_0}(\xi(0), 0) = 0$ for initial mode $r_0$, we obtain
\[
\mathcal{J}_T^2 = \sum_{k=0}^{T} E\left\{z^T(k)z(k) - \gamma^2 \omega^T(k)\omega(k) - V_{r_k}(\xi(k), k)\right\} \\
+ \sum_{k=0}^{T} E\left\{V_{r_{k+1}}(\xi(k+1), k+1)|\xi(k), r_k = i\right\} \\
- E\left\{V_{r_{T+1}}(\xi(T+1), T+1)\right\}. 
\]
On the other hand, for $r_k = i$ and $r_{k+1} = j$, we have
\[
E\left\{V_{r_{k+1}}(\xi(k+1), k+1)|\xi(k), r_k = i\right\} - V_{r_k}(\xi(k), k) \\
= \sum_{j=1}^{N} Pr\{r_{k+1} = j|r_k = i\}\xi^T(k+1)P_j \\
\times \xi(k+1) - \xi^T(k)P_j\xi(k) \\
= \xi^T(k+1)P_j\xi(k+1) - \xi^T(k)P_j\xi(k)
\]
where $P_i$ is defined in (16). By Lemma 2, we obtain
\[
g^T(\xi(k))P_jg(\xi(k)) \leq \xi^T(k)P_j\xi(k).
\]
Considering (9) and combining with (17)–(19) yield the following inequalities:
\[
\mathcal{J}_T^2 \leq E\left\{\sum_{k=0}^{T} \left[\begin{array}{c}
\xi^T(k+1) \\
\xi^T(k)
\end{array}\right]\right\} \\
\left[\begin{array}{c}
P_i \\
\Psi_i \end{array}\right]\left[\begin{array}{c}
\xi^T(k+1) \\
\xi^T(k)
\end{array}\right] \\
= \left[\begin{array}{cc}
P_i \\
\Psi_i
\end{array}\right]
\]
where $\Psi_i$ is defined in (16). By $\Psi_i < 0$ in (16), we have $\mathcal{J}_T^2 < 0$ for all nonzero $\omega(k) \in C_2[0, \infty)$. The proof is completed as $T \to \infty$.

We now shift our design focus to the full-order and the reduced-order DOFC in (11). A sufficient condition for the existence of such a DOFC for an associated Markovian jump nonlinear system (10) is presented as follows.

**Theorem 2:** Given a constant $\gamma > 0$, the closed-loop system (12) is stochastically stable with an $H_\infty$ disturbance attenuation level $\gamma$ if there exist matrices $0 < P_i \triangleq [p_{\alpha\beta}]_i \in R^{(n+s) \times (n+s)}$, $R_i = R_i^T \triangleq [r_{\alpha\beta}]_i \in R^{(n+s) \times (n+s)}$, and $\mathcal{P}_i > 0$, $\alpha, \beta \in \{1, 2, \ldots, (n+s)\}$, such that, for all $i \in N$, the following inequalities are satisfied:

\[
\begin{bmatrix}
M_i & 0 \\
0 & I
\end{bmatrix} \preceq \begin{bmatrix}
-P_i & 0 & 0 & \tilde{\beta}_i \\
* & -\omega_i & 0 & 0 \\
* & * & -2I & \Phi_i \mathcal{K}_i \\
* & * & * & -\gamma^2 I
\end{bmatrix} \\
\begin{bmatrix}
I \\
0
\end{bmatrix} \preceq \begin{bmatrix}
-P_i & 0 & 0 & \tilde{\beta}_i \\
* & -\omega_i & 0 & 0 \\
* & * & -2I & \Phi_i \mathcal{K}_i \\
* & * & * & -\gamma^2 I
\end{bmatrix}
\]

\[
\begin{bmatrix}
I \\
0
\end{bmatrix} \preceq \begin{bmatrix}
0 & 0 & \tilde{\beta}_i \\
* & -\omega_i & 0 \\
* & * & -2I & \mathcal{K}_i D_i \\
* & * & * & -\gamma^2 I
\end{bmatrix} \preceq \begin{bmatrix}
0 & 0 & \tilde{\beta}_i \\
* & -\omega_i & 0 \\
* & * & -2I & \mathcal{K}_i D_i \\
* & * & * & -\gamma^2 I
\end{bmatrix}
\]

\[
p_{\alpha\beta i} - \sum_{\beta \neq \alpha} (p_{\alpha\beta i} + 2r_{\alpha\beta i}) \geq 0 \quad \forall \alpha \\
r_{\alpha\beta i} \geq 0 \quad \forall \alpha \neq \beta \\
p_{\alpha\beta i} + r_{\alpha\beta i} \geq 0 \quad \forall \alpha \neq \beta \\
P_i \mathcal{P}_i = I.
\]

Moreover, if the aforementioned conditions hold, then the system matrices of DOFC (11) are given by $\mathcal{G}_i \triangleq \begin{bmatrix}
\tilde{D}_i & \tilde{C}_i \\
\tilde{B}_i & \tilde{A}_i
\end{bmatrix}$, where

\[
\mathcal{G}_i \triangleq -\Pi_i^{-1}U_i^T \Lambda_i V_i^T (V_i \Lambda_i V_i^T)^{-1} \\
+ \Pi_i^{-1} \Xi_i^T L_i (V_i \Lambda_i V_i^T)^{-1/2} \\
\Lambda_i \triangleq (U_i \Pi_i^{-1}U_i^T - \Psi_i)^{-1} > 0 \\
\Xi_i \triangleq \Pi_i - U_i^T (\Lambda_i - \Lambda_i V_i^T (V_i \Lambda_i V_i^T)^{-1} V_i \Lambda_i) U_i > 0.
\]
In addition, \( \Pi_i \) and \( L_i \) are any appropriate matrices satisfying \( \Pi_i > 0, \| L_i \| < 1 \), and

\[
\Psi_i \triangleq \begin{bmatrix}
-\hat{\Phi}_i^{-1} & 0 & \hat{\Phi}_i \\
0 & -I & \hat{C}_i \\
* & * & -P_i \Phi_i^T K_i 0 \\
* & * & * & -2I \\
* & * & * & -\gamma^2 I
\end{bmatrix},
I_i \triangleq \begin{bmatrix}
I_p \\
0_{s \times p}
\end{bmatrix}
\]

which implies, in view of Lemma 3, that the positive definite matrices \( P_i \) are diagonally dominant. On the other hand, if conditions (20)–(25) are satisfied, the parameters of an \( H_{\infty} \) output feedback controller corresponding to a feasible solution can be obtained using the results in [9]. This completes the proof.

**Remark 2:** The result in Theorem 2, in fact, includes the reduced-order dynamic output feedback control design. In (11), the reduced-order output feedback controller is designed when \( s < n \).

**Remark 3:** It is worth noting that the convex optimization algorithm cannot be used to find a minimum \( \gamma \) since the conditions are no longer linear matrix inequalities (LMIs) due to the matrix equation (25). However, we can solve this problem by using the CCL algorithm proposed in [8]. The core idea of the CCL algorithm is that, if the following inequality:

\[
\begin{bmatrix}
P_i & I & P_i
\end{bmatrix} \geq 0, \quad \forall i \in \mathcal{N}
\]

(30)
is solvable for \( P_i > 0 \) and \( P_i > 0 \), \( \forall i \in \mathcal{N} \), then \( \text{tr}(\sum_i P_i P_i^*) \geq n \); moreover, \( \text{tr}(\sum_i P_i P_i^*) = n \) if and only if \( P_i P_i^* = I \).

From the aforementioned discussion, we can solve the non-convex feasibility problem by formulating it into a sequential optimization problem.

**The Quantized \( H_{\infty} \) DOFC Design Problem:**

\[
\min \quad \text{tr}\left( \sum_i P_i P_i^* \right)
\]

subject to \( (20)–(24) \) and (30).

If there exist solutions that min \( \text{tr}(\sum_i P_i P_i^*) \) is subject to (20)–(24) and \( \text{tr}(\sum_i P_i P_i^*) = n \), then the inequalities in Theorem 2 are solvable.

Therefore, we propose the following algorithm to solve the aforementioned problem.

**Step 1:** Find a feasible set \((P_i^{(0)}, P_i^{(0)}, R_i^{(0)})\) satisfying \((20)–(24)\) and \((30)\). Set \( \kappa = 0 \).

**Step 2:** Solve the following optimization problem:

\[
\min \quad \text{tr}\left( \sum_i \left( P_i^{(\kappa)} P_i + P_i^* P_i^{(\kappa)} \right) \right)
\]

subject to \( (20)–(24) \) and (30).

and denote the optimum value as \( f^* \).

**Step 3:** Substitute the obtained matrix variables \((P_i, P_i^*, R_i)\) into \((20)\) and \((21)\). If \((20)\) and \((21)\) are satisfied with

\[
|f^* - 2N(n + s)| < \delta
\]

for a sufficiently small scalar \( \delta > 0 \), then output the feasible solutions \((P_i, P_i^*, R_i)\), and \( \text{EXIT} \).

**Step 4:** If \( \kappa > N \), where \( N \) is the maximum allowed iteration number, then \( \text{EXIT} \).

**Step 5:** Set \( \kappa = \kappa + 1 \), \((P_i^{(\kappa)}, P_i^{(\kappa)}, R_i^{(\kappa)}) = (P_i, P_i^*, R_i)\), and go to \text{Step 2} \).
Remark 4: Note that, in the aforementioned algorithm, an iteration method has been employed to solve the minimization problem instead of the original nonconvex feasibility problem addressed in (25). In order to solve the minimization problem, the stopping criterion $|f^* - 2N(n+s)|$ should be checked since it can be numerically difficult to obtain the optimal solutions to meet the condition that $\text{tr}(\sum_i P_i P_i) = n$.

IV. ILLUSTRATIVE EXAMPLE AND SIMULATION

In this section, we demonstrate the effectiveness of the proposed quantized output feedback control scheme by a PH semi-Markov model over CR networks (see Fig. 1). It is observed in [20] that CR systems hold promise in the design of large-scale systems due to huge needs of bandwidth during interaction and communication between subsystems. Each channel has two states (busy and idle), and the numbers of times that the channel stays in each state are independent and identically distributed random variables following certain probability distribution functions that have possible connection to both the states and communication between subsystems. Each channel has systems due to huge needs of bandwidth during interaction

A semi-Markov process has been employed in [20] for the CR structure to represent the switch between idle and busy states.

In the following, we consider a semi-Markovian jump non-linear system (10) with two modes over CR links.

Mode 1:

$A_1 = \begin{bmatrix} -4.0 & 1.0 \\ -12 & -2.0 \end{bmatrix}, \quad B_1 = \begin{bmatrix} 1.2 \\ 0.5 \end{bmatrix}, \quad C_1 = \begin{bmatrix} 1.1 & -0.2 \end{bmatrix}$

$D_1 = 6.2, \quad E_1 = [6.3 \quad 1.0], \quad F_1 = \begin{bmatrix} 0.6 \\ 1.3 \end{bmatrix}$

$K_{11} = 0.1, \quad K_{21} = 0.2.$

Mode 2:

$A_2 = \begin{bmatrix} -2.1 & 10.1 \\ 5.2 & -4.1 \end{bmatrix}, \quad B_2 = \begin{bmatrix} 1.2 \\ 0.3 \end{bmatrix}, \quad C_2 = \begin{bmatrix} 0.2 & 0.75 \end{bmatrix}$

$D_2 = 4.2, \quad E_2 = [0.3 \quad 1.0], \quad F_2 = \begin{bmatrix} 0.5 \\ 1.3 \end{bmatrix}$

$K_{12} = 0.1, \quad K_{22} = 0.3.$

Assume that, at each step, the sensor in CR infrastructure scans only one channel. This assumption avoids the use of costly and complicated multichannel sensors. The sensor first picks a channel to scan. It then transmits the signal through if the channel is idle or stops transmission to avoid collision if otherwise. In addition, we assume that the switch between the modes is governed by a semi-Markov process taking values in \{1, 2\}. In these two models, the sojourn times are the random variables distributed according to a negative exponential distribution with parameter $\lambda_1$ and according to a two-order Erlang distribution, respectively. The analysis of a PH semi-Markov switching system, by Lemma 1, is reduced to the analysis of its associated Markovian switching system. The main idea is to search for the associated Markov chain and its infinitesimal generator and define the proper representation.

In particular, two parts can be identified in the second model for the sojourn time which is a random variable exponentially distributed with parameter $\lambda_3$ in part 1 and $\lambda_3$ in part 2. This view suggests that the process $\tilde{r}_k$ must stay at the first part for some time upon entering model 2, before making its way to the second, and finally return to model 1 again. We know that $p_{12} = p_{21} = 1$.

$$
\begin{bmatrix}
p_{11} & p_{12} \\
p_{21} & p_{22}
\end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}, \quad a^{(1)} = \begin{bmatrix} \alpha_1^{(1)} \\ \alpha_2^{(1)} \end{bmatrix} = (1, 0)
$$

$$
T^{(1)} = \begin{bmatrix} T_{11}^{(1)} \\ T_{21}^{(1)} \end{bmatrix} = (\lambda_1)
$$

$$
T^{(2)} = \begin{bmatrix} T_{12}^{(2)} \\ T_{21}^{(2)} \end{bmatrix} = \begin{bmatrix} -\lambda_2 & \lambda_2 \\ 0 & -\lambda_3 \end{bmatrix}.
$$

It is easy to see that the state space of $Z(k) = (\tilde{r}_k, J(k))$ is $G = ((1, 1), (2, 1), (2, 2))$. We enumerate the elements of $G$ as $\varphi((1, 1)) = 1, \varphi((2, 1)) = 2, \varphi((2, 2)) = 3$. Hence, the infinitesimal generator of $\varphi(Z(k))$ is $Q = \begin{bmatrix} -\lambda_1 & \lambda_1 & 0 \\ 0 & -\lambda_2 & \lambda_2 \\ 0 & 0 & -\lambda_3 \end{bmatrix}$.

Now, let $r_k = \varphi(Z(k))$. Then, $r_k$ is the associated Markov chain of $\tilde{r}_k$ with state space \{1, 2, 3\}. The infinitesimal generator of $r_k$ is given by $Q$.

Consider the reduced-order DOFC design, i.e., $s = 1 < n$. As shown in Fig. 2, before entering the controller via the CR network, the signal $y(k)$ is quantized by the mode-dependent logarithmic quantizer (5). The quantizer density is chosen as $\rho^{(1)} = 0.6067, \rho^{(2)} = 0.7391$, and $\eta_0^{(1)} = \eta_0^{(2)} = 0.001$. It can be calculated that $\delta^{(1)} = 0.4$ and $\delta^{(2)} = 0.5$. Solving the quantized $H_\infty$ DOFC problem by means of the designed algorithm of quantized $H_\infty$ DOFC implies that the minimum $\gamma$ is equal to $\gamma^* = 2.304$, and the corresponding reduced-order DOFC parameters are designed as

$$
\dot{A}_1 = -1.204, \quad \dot{B}_1 = 3.830, \quad \dot{C}_1 = -3.372, \quad \dot{D}_1 = -0.537
$$

$$
\dot{A}_2 = -1.067, \quad \dot{B}_2 = 1.155, \quad \dot{C}_2 = -2.316, \quad \dot{D}_2 = 4.071.
$$

Now, we illustrate the effectiveness of the quantized full-order DOFC designed in (11) through simulations. The repeated scalar nonlinearity in (10) is chosen as $g(x(k)) = \sin(x(k))$, which satisfies (4). Let the initial conditions be $x(0) = [1.1 - 0.5]^T$ and $\dot{x}(0) = 0$. The disturbance input $\omega(k)$ is assigned as $\omega(k) = 0.1e^{-2k}$. 

![Fig. 2. Structure of a quantized closed-loop system with CR networks.](image-url)
The simulation results are shown in Figs. 3–7. Fig. 3 displays a switching signal; here, “1” and “2” correspond to the first and second modes, respectively. Under this mode sequence, the trajectories of $y(k)$ and quantized measurements $q(y(k))$ are shown in Fig. 4. It can be seen that the mode-dependent quantizer is adjusted according to the mode jumping sequences. The trajectory of $q_s^i(y(k))$ is demonstrated in Fig. 5. To further illustrate the effectiveness of the proposed technique, we perform the Monte Carlo simulation. In Figs. 6 and 7, the state responses of the closed-loop system and the full-order DOFC for 50 runs are shown, respectively. The semi-Markov processes are unique in each run. It can be seen that the system is stochastically stabilized for every run of simulation.

V. CONCLUSION

In this paper, the problem of quantized output feedback control has been addressed for a class of S-MJSs with repeated scalar nonlinearities. A mode-dependent logarithmic quantizer has been employed to quantize the measured output signal. Then, using the positive definite diagonally dominant Lyapunov function technique, a sufficient condition has been proposed to ensure the stochastic stability with an $H_\infty$ performance for the closed-loop system. Furthermore, a sufficient condition has been decoupled into a convex optimization problem, which can be efficiently handled using standard numerical software. The corresponding mode-dependent quantized controller has
been successfully designed for nonlinear S-MJSs. Based on CR communication networks, an example has been provided to illustrate the applicability of the proposed techniques.

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