IEEJ TRANSACTIONS ON ELECTRICAL AND ELECTRONIC ENGINEERING
IEEJ Trans 2019
Published online in Wiley Online Library (wileyonlinelibrary.com). DOI:10.1002/tee.22989

Paper

Classification-Based Control for Wireless Networked Control Systems with Lossy Multipacket Transmission

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A classification-based control approach is proposed for wireless networked control systems with lossy multipacket transmission. This approach takes advantage of a state reconstruction process to deal with the distinct feature of partial failure of data transmission caused by multipacket transmission, and then classifies the difference of the latest received system states and reconstructed ones to design a classification-based controller. The closed-loop stability of the system is proven using the switched systems theory. By considering more communication characteristics of multipacket transmission, the proposed approach is shown to give rise to a better system performance by a numerical example.

Keywords: networked control system; multipacket transmission; packet dropout; partial failure; classification

Received 6 December 2018; Revised 21 February 2019

1. Introduction

The so-called Networked Control Systems (NCSs) whose control links are closed via some non-control-dedicated communication networks have long been a hot research field since its first introduction several decades ago. The integration with communication networks results in a novel control structure for NCSs, and enables the flexibility of system expansion, the capability of remote operation, the ease of maintenance, and so forth [1,2]. Example application areas of NCSs include automated highway systems, micro-electro-mechanical systems, Internet of Things, intelligent factory, and much more [3,4], and the applications are flourishing in the coming future due to the fast convergence of control, communication, and computation. It is realized, however, the introduction of communication networks to control systems has fundamentally modified the data transmission mode [5], i.e., the lossless data transmission taken for granted in conventional systems is now impossible in NCSs, because of the limited network bandwidth, the competition of data transmission, the lossy data transmission channel, and other limiting factors in communication networks. The lossy data transmissions in NCSs degrade dramatically the control system performance if no special treatment is taken into account for NCSs, inspiring consequently a great number of works and efforts from the control community to address these problems.

Data packet dropout, one common issue in data communication networks, can arise from transmission errors, congestion in the physical communication links, or buffer overflows [6,7]. The communication network used in NCSs also suffers from data packet dropout, be it sensing data packet or control data packet. Data packetx dropout in NCSs can make either the sensing data unavailable to the controller, or the control signal unavailable to the actuator, which then consequently severely degrade control system performance or even destabilize the system. Considerable works have been reported in recent years to deal with this issue. To name a few, an interval type-2 model-based approach is used for nonlinear NCSs with packet dropouts [8]; a model predictive control based framework is presented to compensate for packet dropout [9]; a coarsest quantizer is proposed to stabilize wireless NCSs with random packet losses [10], and a lot more other works have made their contributions from various perspectives.

With the increasing use of wireless communications in NCSs, one may notice that a new form of data packet dropout arises. Indeed, in wireless NCSs, it is popular to use multiple independent sensors to sample the plant, and these sensors transmit their sensing data to the controller via the communication network independently, referred to as 'multi-packet transmission'. Even though the communication networks that different sensors use for the sensing data transmission are the same, the sensing data still face different network conditions due to the stochastic nature of the communication channel. This then means that at some time instant, the sensing data from some sensors are transmitted successfully while those from other sensors are lost. Consequently, this partial successful transmission produces partially available plant information at the controller, a distinct feature caused by multipacket transmission in NCSs [11–14], which fails most existing studies on data packet dropout that are lack of special and dedicated treatments.

The above discussion motivates our present work on NCSs with data packet dropout under multipacket transmission. In our previous work [15], the partially unavailable sensing data are reconstructed at the controller side and then a feedback control law is designed within the stochastic control framework for the data transmission of each sensor being Bernoulli. Such a common feedback gain can be convenient to design, but it is noticed that the reconstructed and the practically observed system states are not at the same level of accuracy. This fact then means that applying different feedback gains to different parts of system states, i.e., latest received or reconstructed, may improve the

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system performance, thus motivating our present work on a classification-based control approach. Specifically, this approach still reconstructs the partially unavailable sensing data at the controller side, but the feedback gains are designed separately for the reconstructed part and the latest received part of the system states. Also, we drop the somehow inconvenient Bernoulli assumption of the sensing data transmission [15], and transform the system setting into the switched system framework rather than the stochastic control framework [15]. Hence, the present work provides a distinct perspective and approach for the data packet dropout issues under multipacket transmission in NCSs.

The remainder of the article is organized as follows. Section 2 formulates the problem and Section 3 proposes the classification-based control method to NCSs with lossy multipacket transmission. The stability conditions and the controller design approach are obtained in Section 4. A numerical example is discussed in Section 5 to illustrate the effectiveness of the proposed approach and Section 6 concludes the paper.

2. Problem Formulation

2.1. The system under study The considered NCS is depicted in Fig. 1, where p independent sensors sample the plant and send the sensing data via competitive and imperfect communication networks with possible data loss while the communication channel from the controller to the actuator is assumed lossless. Such a system setting is practically sound since the 'imperfection' of transmitting the sensing data is mainly caused by the access competition of the channel, which is absent for transmitting the control data. For more discussion of this system setting, one may refer to Remark 3 of our previous work [15].

The plant is described by the following linear discrete-time invariant system,

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

where $x(k) \in \mathbb{R}^n$ is the state vector, $u(k) \in \mathbb{R}^m$ is the control input, $A \in \mathbb{R}^{n\times n}$ is the system matrix, and $B \in \mathbb{R}^{n\times m}$ is the input matrix.

From the discussions in Remark 1, we may assume that the system state $x(k)$ is constructed by sequentially placing the sensing data, i.e.,

$$x(k) = [(x^1(k))^T, (x^2(k))^T, \ldots, (x^p(k))^T]^T$$

where $x^i(k) \in \mathbb{R}^{c_i}, i = 1, 2, \ldots, p$ is the sensing data from sensor i at time k, and $\sum_{i=1}^{p} c_i = n$.

As assumed, $x^i(k)$ may be lost during transmission, which is modeled by an indicator α_k^i, as follows,

$$\alpha_k^i = \begin{cases} 0 & x^i(k) \text{ is lost} \\ 1 & \text{otherwise} \end{cases} \tag{2}$$

Define the indicator vector as $[\alpha_k^1, \alpha_k^2, \ldots, \alpha_k^p]^T \in \mathbb{I}$ where $\mathbb{I} = \{[\sigma_1, \ldots, \sigma_i, \ldots, \sigma_p]^T : \sigma_i = 0, 1, i = 1, \ldots, p\}$. This indicator vector specifies explicitly whether the data from sensor i, $i = 1, \ldots, p$ are transmitted successfully or not. Note that $\mathbb{I}$ contains $q = 2^p$ elements.

Remark 1. One may notice that the system state *x(k)* consists of the sensing data from p sensors, but the elements in *x(k)* may not be necessarily listed sequentially with the sensors from 1 to p. Luckily, it is a fact that whatever the elements in *x(k)* are ordered, one may always perform a permutation to exchange between any two *x(k)* with different ordering. Such a permutation corresponds to an invertible linear transformation, and such a transformation can be safely done without affecting any system level properties such as stability, robustness, etc. Therefore, we will, without loss of generality, assume that *x(k)* is ordered in such a way that the sensing data are sequentially listed from sensor 1 to p.

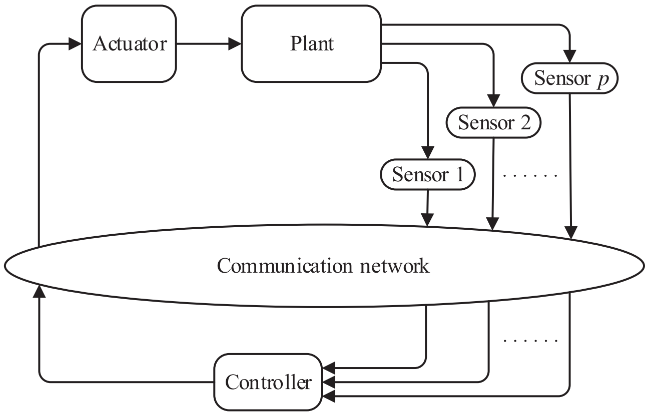

Fig. 1. Networked control systems with multipacket transmission

2.2. The effects of multipacket transmission on system design For a control system with lossy single-packet transmission in NCSs, the conventional state feedback law is typically obtained as follows

$$u(k) = K\widetilde{x}(k) \tag{3}$$

where the feedback gain K is time-invariant. When $x(k)$ is not available due to packet dropout or delay, we may either use the value at the previous step [16].

$$\widetilde{x}(k) = \begin{cases} x(k) & x(k) \text{ is available} \\ \widetilde{x}(k-1) & \text{otherwise} \end{cases}$$

or zero value [17].

$$\widetilde{x}(k) = \begin{cases} x(k) & x(k) \text{ is available} \\ 0 & \text{otherwise} \end{cases}$$

The above two strategies usually work well for conventional single-packet transmission scenario. However, in the presence of lossy multipacket transmission, we face a completely different situation, i.e., $x(k)$ may not be entirely available to the controller at time k, but some part of it can be available due to the partial successful transmission. Such a fact means that the traditional treatment as above for data packet dropout can be too conservative, unfortunately ignoring much information available for the controller.

To deal with this issue, in this work we take advantage of a system state reconstruction method to reconstruct the partial lost information (Section 3), an effective way to take use of all available information to the controller [14].

Such a state reconstruction method is in the open-loop fashion due to the loss of the needed information, which then means that the above conventional control strategies can still be conservative even equipped with reconstructed system states. A novel controller with special consideration of the reconstructed system states to improve the control performance is, therefore, needed, as proposed in this present work.

3. Classification-Based Control for NCSs with Multipacket Transmission

3.1. The classification-based control approach The classification-based control approach consists three modules: the network state detector, the sensing data reconstruction module, and the classification-based controller, as depicted in Fig. 2. Data packet dropout is first detected by the network state detector and α_k^i in (2) is specified, the system state is then reconstructed

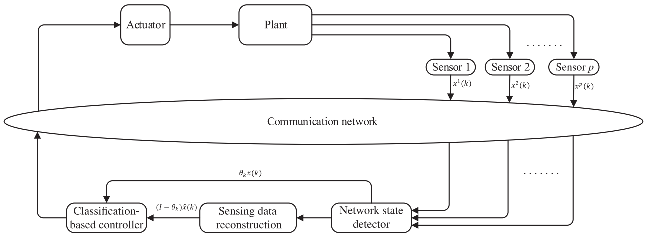

Fig. 2. The diagram of the classification control law for NCSs with multipacket transmission

by the system state reconstruction module [14], and finally the classification-based controller is designed.

For the system state reconstruction process, we split the system matrix A and the input matrix B in (1) into $p \times p$ and $p \times 1$ block matrices,

$$A = \begin{bmatrix} A^{11} & A^{12} & \dots & A^{1p} \\ A^{21} & A^{22} & \dots & A^{2p} \\ \vdots & \vdots & \ddots & \vdots \\ A^{p1} & A^{p2} & \dots & A^{pp} \end{bmatrix}, \quad B = \begin{bmatrix} B^1 \\ B^2 \\ \vdots \\ B^p \end{bmatrix} \tag{4}$$

where $A^{ij} \in \mathbb{R}^{c_i \times c_j}$, $i = 1, 2, \dots, p, j = 1, 2, \dots, p$, and $B^i \in \mathbb{R}^{c_i \times m}$. Then,

$$x^i(k+1) = \sum_{j=1}^{p} A^{ij} x^j(k) + B^i u(k) \tag{5}$$

where $i = 1,\ 2,\ \dots,\ p$.

As assumed, $x^j(k)$ may not be available to the controller for some j. Denote $\widehat{x}^i(k+1)$ the reconstructed state of sensor i at time $k+1$, and then

$$\widehat{x}^i(k+1) = \sum_{j=1}^{p} A^{ij} \overline{x}^j(k) + B^i u(k) \tag{6}$$

where $\overline{x}^j(k) = \alpha_k^j x^j(k) + (1-\alpha_k^j)\widehat{x}^j(k)$.

Define $\overline{x}^T(k) = [\{\overline{x}^1(k)\}^T, \{\overline{x}^2(k)\}^T, \dots, \{\overline{x}^p(k)\}^T]$. It then follows that

$$\overline{x}(k) = \Theta_{\sigma(k)} x(k) + (I - \Theta_{\sigma(k)})\widehat{x}(k) \tag{7}$$

where $\sigma(k) \in \mathbb{I}$ and

$$\Theta_{\sigma(k)} = \begin{bmatrix} \alpha_k^1 I^{c_1 \times c_1} & & & \\ & \alpha_k^2 I^{c_2 \times c_2} & & \\ & & \ddots & \\ & & & \alpha_k^p I^{c_p \times c_p} \end{bmatrix} \tag{8}$$

It follows that (6) can be written in a compact form,

$$\widehat{x}(k+1) = A\overline{x}(k) + Bu(k) \tag{9}$$

We acknowledge that a control system usually uses only the latest system state and control signal information due to the real-time requirement. The above model-based compensation scheme can reconstruct partial lost information caused by multipacket transmission, which is, however, based on the old sensing data and is thus not as 'good' as the newly arrived data. A real-time controller needs to clarify these different signals and use only the latest information, yielding the so-called clarification-based control law, as follows,

$$u(k) = K_1 \Theta_{\sigma(k)} x(k) + K_2 (I - \Theta_{\sigma(k)})\widehat{x}(k) \tag{10}$$

where $K_1,\ K_2 \in \mathbb{R}^{n \times m}$ are different control gains for real and reconstructed system states.

3.2. The closed-loop system By defining $\eta^T(k) = [x^T(k), \widehat{x}^T(k)]$, from (1),(7), (9), and (10), the closed-loop NCS is obtained as

$$\eta(k+1) = \Phi_{\sigma(k)} \eta(k) \tag{11}$$

where

$$\Phi_{\sigma(k)} = \begin{bmatrix} A + BK_1\Theta_{\sigma(k)} & BK_2(I - \Theta_{\sigma(k)}) \\ (A + BK_1)\Theta_{\sigma(k)} & (A + BK_2)(I - \Theta_{\sigma(k)}) \end{bmatrix} \tag{12}$$

4. Stability Analysis and Controller Design

Switched system theory is applied to the closed-loop system in (12) for the stability criteria, following which a controller design method is proposed.

4.1. Stability analysis The following exponential stability concept is introduced.

Definition 1. A switched system $\eta(k+1) = \Phi_{\sigma(k)}\eta(k)$ is said to be exponentially stable with a decay rate μ satisfying $0 < \mu < 1$, if its solution $\eta(k)$ satisfies $\|\eta(k)\| \le c\mu^k \|\eta(0)\|$, where $c > 0$ is a constant.

Let the symbols $>$ and $<$ in the context of matrices mean positive and negative definite, respectively. We have the following stability result.

Theorem 1. For given controller gain matrices $K_1,\ K_2 \in \mathbb{R}^{m \times n}$, the closed-loop system in *(11)* is exponentially stable with decay rate $\mu = \sqrt{1-\upsilon}$, $0 < \upsilon < 1$, if there exist positive definite matrices $P_i \in \mathbb{R}^{2n \times 2n}$ and scalar $\beta > 0$ such that $\beta I < P_i < I$ and

$$\begin{bmatrix} -P_i + \upsilon I & \Phi_i^T \\ \Phi_i & -P_j^{-1} \end{bmatrix} < 0, \forall (i,j) \in \mathbb{I} \times \mathbb{I} \tag{13}$$

Proof: Define the following indicator function

$$\varepsilon^T(k) = [\varepsilon_0(k), \varepsilon_1(k), \dots, \varepsilon_q(k)]$$

with

$$\varepsilon_i(k) = \begin{cases} 1 & \sigma(k) = i \\ 0 & \text{otherwise} \end{cases} \tag{14}$$

The control system in (11) can be rewritten as

$$\eta(k+1) = \sum_{i=0}^{q} \varepsilon_i(k) \Phi_i \eta(k) \tag{15}$$

For the switched system in (15), the corresponding switched Lyapunov function is defined as follows,

$$V(k, \eta(k)) = \eta^T(k) P(\varepsilon(k)) \eta(k) \tag{16}$$

where $P(\varepsilon(k)) = \sum_{i=0}^{q} \varepsilon_i(k) Q_i$ and $Q_i > 0$. From (14), we can further obtain

$$V(k, \eta(k)) = \eta^T(k) Q_i \eta(k)$$

Let $\beta_0 = \min \cup_{i \in \mathbb{I}} \lambda(Q_i)$ and $\rho_0 = \max \cup_{i \in \mathbb{I}} \lambda(Q_i)$ where $\lambda(Q_i)$ is the set of the eigenvalues of Qi. Notice that $\beta_0 > 0$ and $\rho_0 > 0$, and hence there always exit $\beta_0 > \beta_1 > 0$ and $\rho_1 > \rho_0 > 0$ such that

$$\beta_1 I < Q_i < \rho_1 I \tag{17}$$

$$\beta_1 \|\eta(k)\|^2 < V(k, \eta(k)) < \rho_1 \|\eta(k)\|^2 \tag{18}$$

Hence, it is obtained that

$$\Delta V = V(k+1, \eta(k+1)) - V(k, \eta(k))$$

$$= \eta^T(k+1)P(\varepsilon(k+1))\eta(k+1) - \eta^T(k)P(\varepsilon(k))\eta(k)$$
$$= \eta^T(k)(\Phi_i^T P(\varepsilon(k+1))\Phi_i - P(\varepsilon(k)))\eta(k)$$
$$= \eta^T(k)(\Phi_i^T Q_j \Phi_i - Q_i)\eta(k) \tag{19}$$

Let $\upsilon_0 = \min \cup_{(i,j)\in \mathbb{I}\times\mathbb{I}} \lambda(Q_i - \Phi_i^T Q_j \Phi_i) > 0$ and $0 < \upsilon_1 < \upsilon_0$. Then

$$V(k, \eta(k)) - V(k+1, \eta(k+1)) > \upsilon_1 \|\eta(k)\|^2 \tag{20}$$

From (18) and (20) it follows that

$$\beta_1 \|\eta(k)\|^2 - \rho_1 \|\eta(k+1)\|^2 > \upsilon_1 \|\eta(k)\|^2$$

that is,

$$\|\eta(k+1)\|^2 < \left(\frac{\beta_1}{\rho_1} - \frac{\upsilon_1}{\rho_1}\right)\|\eta(k)\|^2$$

From the inequality $0 < \frac{\beta_1}{\rho_1} < 1$, we obtain the following inequality,

$$\|\eta(k+1)\|^2 < \left(1 - \frac{\upsilon_1}{\rho_1}\right)\|\eta(k)\|^2$$

Let $\mu = \sqrt{1 - \frac{\upsilon_1}{\rho_1}}$, we then obtain

$$\|\eta(k)\|^2 < \mu^{2k}\|\eta(0)\|^2$$

or equivalently, $\|\eta(k)\| < \mu^k \|\eta(0)\|$.
Inequalities (17) and (20) can be rewritten as

$$\frac{\beta_1}{\rho_1} I < \frac{1}{\rho_1} Q_i < I$$

$$\begin{bmatrix} -Q_i + \upsilon_1 I & \Phi_i^T \\ \Phi_i & -Q_j^{-1} \end{bmatrix} < 0 \tag{21}$$

Then premultiplying and postmultiplying (21) with

$$\begin{bmatrix} \frac{1}{\sqrt{\rho_1}} & 0 \\ 0 & \sqrt{\rho_1} \end{bmatrix}$$

and its transpose yields

$$\begin{bmatrix} -\frac{1}{\rho_1} Q_i + \frac{\upsilon_1}{\rho_1} I & \Phi_i^T \\ \Phi_i & -\rho_1 Q_j^{-1} \end{bmatrix} < 0 \tag{22}$$

Define new variables $\upsilon = \frac{\upsilon_1}{\rho_1}$, $\beta = \frac{\beta_1}{\rho_1}$, and $P_i = \frac{1}{\rho_1} Q_i$. (13) and $\beta I < P_i < I$ can, therefore, be obtained. The proof is thus completed.

4.2. Controller design

In this section, the design problem of the control gain matrices K_1, K_2 in (10) is considered. The basic idea is that the decay rate μ of the closed-loop control system is optimized and the different control gain matrices are then obtained. Before deriving the controller design method, the following lemma from [18] is needed.

Lemma 1. For given matrices *X, Y, Z* with appropriate dimensions where $X = X^T > 0$ and $Z = Z^T > 0$, the following inequality holds

$$\begin{bmatrix} -X & Y^T \\ Y & -Z^{-1} \end{bmatrix} < 0 \tag{23}$$

if there exists $\gamma > 0$ such that

$$\begin{bmatrix} -X & \gamma Y^T & 0 \\ \gamma Y & -2\gamma I & Z \\ 0 & Z & -Z \end{bmatrix} < 0 \tag{24}$$

■

With Lemma 1, the following Theorem can be readily obtained, whose proof is thus omitted. Theorem 2 provides the explicit controller design procedure.

Theorem 2. The closed-loop system in (11) with the controller in (10) is exponentially stable with the decay rate $\mu = \sqrt{1-\upsilon}$ if the following optimization problem is feasible for $0 < \upsilon < 1$,

$$\max \quad \upsilon$$
$$\text{s.t.} \quad \beta I < P_i = P_i^T, P_j = P_j^T < I$$
$$\begin{bmatrix} -P_i + \upsilon I & \gamma {\Phi_i}^T & 0 \\ \gamma \Phi_i & -2\gamma I & P_j \\ 0 & P_j & -P_j \end{bmatrix} < 0, \ \forall (i,j) \in \mathbb{I}\times\mathbb{I}$$

where $0 < \beta < 1, \gamma > 0$, $P_i, i = 1, 2, \ldots, q$, $\widehat{K}_i$ are with appropriate dimensions, and

$$\gamma \Phi_i = \begin{bmatrix} \gamma A + B\widehat{K}_1 \Theta_i & B\widehat{K}_2(I - \Theta_i) \\ (\gamma A + B\widehat{K}_1 \Theta_i & (\gamma A + B\widehat{K}_2)(I - \Theta_i) \end{bmatrix} \tag{25}$$

Furthermore, the control gain matrices can be constructed as follows subject to the feasibility of the above optimization problem,

$$K_i = \frac{\widehat{K}_i}{\gamma}, \quad i = 1, 2 \tag{26}$$

5. Numerical Example

Considering the following open-loop unstable third-order system with disturbance,

$$x(k+1) = Ax(k) + Bu(k) + w(k) \tag{27}$$

where the initial state is set as $x(0) = [-1, -1, 1]^T$, $w(k)$ is a Gauss white noise with the variance being 0.05, and the system matrices are borrowed from the literature [19],

$$A = \begin{bmatrix} -0.850 & 0.271 & -0.488 \\ 0.482 & 0.100 & 0.2400 \\ 0.002 & 0.3681 & 0.7070 \end{bmatrix}, \ B = \begin{bmatrix} 0.5 & 0.1 \\ 0.3 & -0.4 \\ 0.2 & 0.5 \end{bmatrix}$$

In the simulation, we assume that the 3 system states in (27) are sampled and sent by three independent sensors, with the same data loss rate of 0.35.

A typical case of data packet dropout is shown in Fig. 3, from which we may observe that the dropouts of the states $x_i(k)$, $i = 1$, 2, 3 are not synchronous. Hence, at the controller side the whole state $x(k)$ may often be unavailable. This illustrates the challenge we face in the present work.

Using the proposed method in this article, we can obtain the following gain matrices,

$$K_1 = \begin{bmatrix} 0.8445 & -0.5877 & 0.1826 \\ 0.5410 & -0.4863 & -0.7082 \end{bmatrix},$$

$$K_2 = \begin{bmatrix} 0.1036 & -0.1547 & 0.0272 \\ 0.1154 & -0.0185 & -0.1766 \end{bmatrix}.$$

We compare our proposed method with the stochastic control approach [15], which yields the same feedback gain for both reconstructed and observed system states, as follows,

$$K = \begin{bmatrix} 0.5867 & -0.2989 & 0.2927 \\ 0.3289 & -0.2493 & -0.2377 \end{bmatrix}.$$

The state trajectories with both approaches are shown in Fig. 4. It is seen that both approaches ensure the stability of the closed-loop system but the approach proposed in this article evolves more smoothly. This advantage should be credited to the proposed classification-based approach where the latest received system

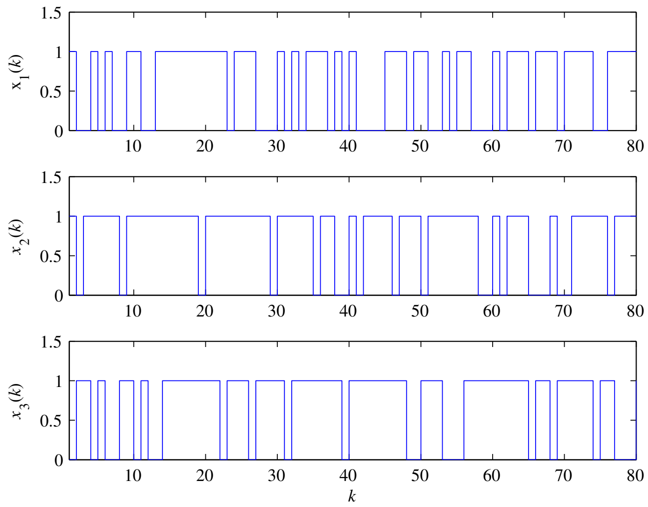

Fig. 3. Illustrating a typical case of data packet dropout. '1' indicates a successful transmission, and '0' vice versa

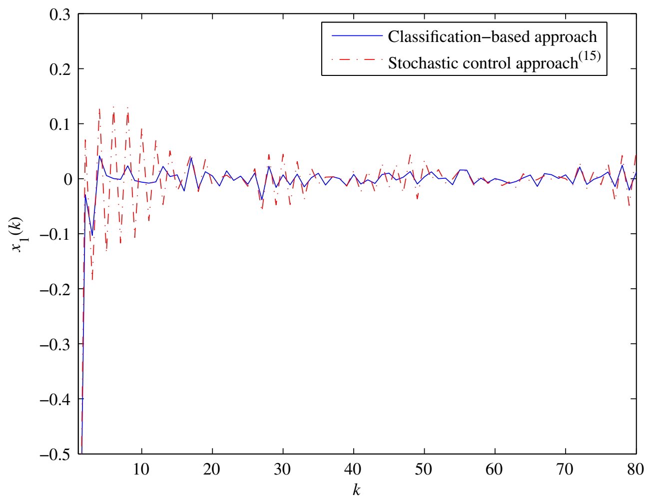

Fig. 4. Comparing the state trajectories of the classification-based approach and the stochastic control approach

Table I. Comparison using extensive simulations

	Percentage of stable trajectory	
Set of loss rate	Classification-based approach (%)	Stochastic control approach [15] (%)
[0.1, 0.1, 0.15]	100	100
[0.2, 0.25, 0.2]	100	100
[0.35, 0.35, 0.35]	100	96
[0.4, 0.4, 0.45]	88	80

A total of 50 simulations are conducted for each loss rate set that contains the loss rate of $x_1(k)$, $x_2(k)$, $x_3(k)$ in order.

states and the reconstructed ones are explicitly classified with different control gains.

To illustrate the effectiveness of the proposed approach further, we conducted a number of simulations with different sets of loss rates. The results shown in Table I show that the proposed approach is generally superior to the non-clarification-based approach [15] in the statistical sense.

6. Conclusions

Multipacket transmission is a common feature for wireless-NCSs with multiple sensors, which produces a challenging issue of partial failure of data transmission. We have proposed a classification-based control approach to deal with this issue. The fundamental idea is to take more consideration of the communication characteristics to facilitate the control design. We find such a philosophy works well in this particular problem and believe it deserves further investigation from various possible perspectives in the future.

Acknowledgments

This work was supported by the National Natural Science Foundation of China under Grant 61673350.

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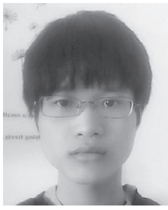

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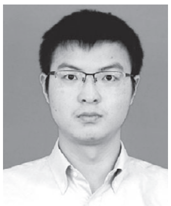

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