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A compensation method for the packet loss deviation in system identification with event-triggered binary-valued observations

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Dear editor,
With the rapid development of network and communication technology, group systems interrelated in terms of both time and space are commonly encountered, such as sensor networks, multi-agent systems, and smart power grids. How to save communication resources among systems has become a very important and urgent issue. The thought of "event-trigger" has come into being, where an "event" is defined to determine whether the measured data are "useful enough" for a particular purpose. Only when the event is triggered, the data will be sent to an estimation/control center over a communication network. Several studies have demonstrated the distinct advantages of the event-triggered mechanism in the optimization and utilization of communication resources because the additional information is provided by the event-trigger condition despite having no communication at the un-triggered time [1].

However, when the estimation/control center does not receive data, it is unable to judge which situation happens: the "event" is not triggered; or the "event" is triggered but the data is lost during the communication. This may lead to the improper use of the triggered condition, which poses new challenges. To address this problem, this study proposes a deviation compensation technique for system identification with binary-valued observations. An identification algorithm is constructed, and its strong convergence and communication rate are given as well. Numerical simulation is also included to illustrate the obtained results.

Recently, related studies have achieved significant developments. For example, Ref. [2] used the maximum likelihood method to study identification of ARMA systems based on finitely quantized output observations with packet dropouts. Under both the binary-valued quantization and the communication unreliability, Ref. [3] investigated recursive identification of FIR systems. Ref. [4] handled parameter estimation under event-triggered binary-valued observations for FIR systems. Interested readers can also refer to [5–7] and the references therein. Most of the existing work focused on at most two of the following three factors: quantization, event-triggered scheme, and communication uncertainty. This study essentially proposes an attempt to deal with all three simultaneously

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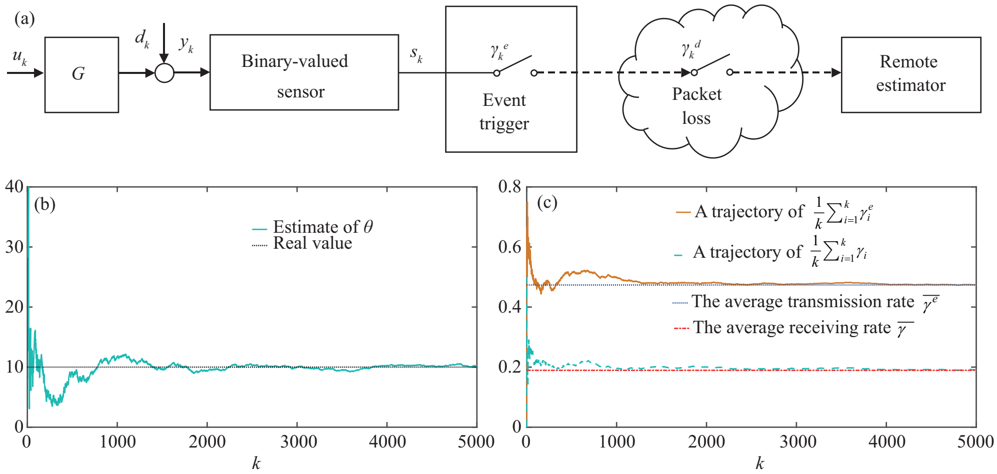

Figure 1 (Color online) System set-up and simulation results. (a) System set-up; (b) convergence of $\widehat{\theta}_k$; (c) communication rate.

for system identification.

System set-up. Consider the system

$$y_k = G(u_k;\theta) + d_k,$$

where u_k is the input, θ is the unknown parameter, and d_k is the noise. y_k is the system output, which is measured by a binary-valued sensor, and it can be expressed by the following indicator function:

$$s_k = I_{\{y_k \leqslant C\}} = \begin{cases} 1, \text{ if } y_k \leqslant C, \\ 0, \text{ otherwise}, \end{cases} \quad (1)$$

with a fixed threshold $C \in (-\infty, \infty)$.

As shown in Figure 1(a), a prediction-based event-triggered scheme is employed to decide whether s_k should be sent to the remote estimation center. Let $\gamma_k^e \in \{0,1\}$ denote the transmission indicator, which can be given by

$$\gamma_k^e = \begin{cases} 1, & s_k \neq \widehat{s}_k, \\ 0, & s_k = \widehat{s}_k, \end{cases} \quad (2)$$

where $\widehat{s}_k = I_{\{G(u_k;\widehat{\theta}_{k-1})\leqslant C\}}$ can be seen as the prediction of s_k based on the estimate $\widehat{\theta}_{k-1}$ of θ at time $k-1$, which can be broadcasted by the remote estimator or computed by the sensor itself. Here $\gamma_k^e = 1$ means s_k is transmitted; otherwise, there is no communication at this time.

The communication unreliability may lead to the packet loss during the transmission. Let γ_k^d represent whether this packet is lost, i.e.,

$$\gamma_k^d = \begin{cases} 1, & \text{no packet loss}, \\ 0, & \text{packet loss}. \end{cases}$$

The data received indicator $\gamma_k = \gamma_k^e\gamma_k^d$ is accessible to the estimator, but γ_k^e or γ_k^d is unknown separately. Hence, the available information is $\{\gamma_k\}$ and $\{\gamma_k s_k\}$.

To express the thought clearly, this study constructed a deviation compensation algorithm to estimate θ and established the convergence properties for the following gain system:

$$y_k = u_k\theta + d_k. \quad (3)$$

Without loss of generality, let $u_k \equiv 1$. In fact, the results can be readily extended to the identification of FIR systems, rational transfer functions, Wiener models, and Hammerstein models, as they can be reduced to identify a group of gain systems under appropriately designed periodic inputs [8].

Assumption 1. The system noise sequence $\{d_k\}$ is independent and identically distributed (i.i.d.). Its accumulative distribution function, denoted by $F(\cdot)$, is invertible, and its moment generating function exists. Moreover, the inverse function of $F(\cdot)$ is twice continuously differentiable.

Assumption 2. The packet loss sequence $\{\gamma_k^d\}$ is i.i.d., which follows Bernoulli distribution with a known fixed parameter $p < 1$, i.e., $\Pr(\gamma_k^d = 0) = p$. In addition, $\{\gamma_k^d\}$ is independent of $\{d_k\}$ and $\{\gamma_k^e\}$.

Remark 1. (i) For a fixed network structure and communication payloads, the packet loss probability p is often constant when employed in practical applications. Some methods have been developed to estimate the unknown p [9]. (ii) The cumulative distribution function $F(\cdot)$ of the noise is assumed to be known in Assumption 1. One can refer to the method of joint identification in [8] if it is unknown. (iii) This study only considers the binary-valued observation. In fact, the results can be readily extended to cases of multiple-level quantization as it is possible to view a multi-level quantized observation as a group of binary-valued observations with different thresholds [8].

Identification algorithm. The following deviation compensation algorithm is proposed to estimate θ:

$$\eta_k = \gamma_k s_k - \gamma_k \widehat{s}_k + (1-p)\widehat{s}_k, \quad (4)$$

$$\xi_k = \left(1-\frac{1}{k}\right)\xi_{k-1} + \frac{1}{k}\eta_k, \quad (5)$$

$$\widehat{\theta}_k = C - F^{-1}\left(\frac{\xi_k}{1-p}\right), \quad (6)$$

where the distribution function $F(\cdot)$ and the packet loss rate p is given by Assumptions 1 and 2. C is the threshold in (1). The initial values are $\widehat{s}_0 = 0$ or 1 and $\xi_0 = 1/2$.

Convergence. The proposed theorem establishes the convergence performance of the estimation algorithm.

Theorem 1. Consider the system (3) with binary-valued observation (1), trigger mechanism (2), and a packet loss communication environment under Assumptions 1 and 2. The estimator $\widehat{\theta}_k$ given by (4)–(6) is convergent to the true value θ with probability 1, i.e.,

$$\widehat{\theta}_k \to \theta, \text{ w.p.1 as } k \to \infty.$$

Communication rate. For convenience, define

$$\widetilde{F}(z) = I_{\{z<0\}}F(z) + I_{\{z\geqslant 0\}}(1-F(z)), \quad z \in \mathbb{R},$$

where the function $F(\cdot)$ comes from Assumption 1.

Theorem 2. If the conditions in Theorem 1 hold, then we have

(i) The average transmission rate before the communication channel from the event trigger (2) is convergent, i.e.,

$$\frac{1}{k}\sum_{i=1}^{k}\gamma_i^e \to \widetilde{F}(C-\theta) := \overline{\gamma}^e, \text{ w.p.1 } k \to \infty; \quad (7)$$

(ii) The average receiving rate after the channel is also convergent, i.e.,

$$\frac{1}{k}\sum_{i=1}^{k}\gamma_i^e\gamma_i^d \to (1-p)\widetilde{F}(C-\theta) := \overline{\gamma}, \text{ w.p.1 } k \to \infty.$$

The proofs of Theorems 1 and 2 can be found in Appendix A.

Simulation. We consider the system $y_k = u_k\theta + d_k$ with the binary-valued observation s_k given by (1), where $u_k \equiv 1$, $C = 8$, and $\theta = 10$. $\{d_k\}$ is i.i.d. and obeys normal distribution, where the mean is 0 and the standard deviation is 40. The event-trigger scheme (2) is used to determine whether s_k is sent to the estimation center over a communication network whose packet loss probability is $p = 0.6$. The estimation algorithm (4)–(6) is employed to obtain the estimate $\widehat{\theta}_k$ of unknown parameter θ. Figure 1(b) shows that the algorithm is convergent, and the packet loss deviation can be overcome efficiently. Figure 1(c) illustrates the communication rate. The average transmission rate converges to $\overline{\gamma}^e = 0.4734$, and the average receiving rate converges to $\overline{\gamma} = 0.1894$. Other details regarding our simulation results can be found in Appendix B.

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Supporting information Appendixes A and B. The supporting information is available online at info.scichina.com and link.springer.com. The supporting materials are published as submitted, without typesetting or editing. The responsibility for scientific accuracy and content remains entirely with the authors.

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