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Practice article

An energy-efficient data transmission scheme for remote state estimation and applications to a water-tank system

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ABSTRACT

An energy-efficient data transmission scheme for remote state estimation is proposed and experimentally evaluated in this paper. This new transmission strategy is presented by proving an upper bound of the system performance. Stability of the remote estimator is proved under the condition that some of the observation measurements are lost in a random probability. An experimental platform of two coupled water tanks with a wireless sensor node is established to evaluate and verify the proposed transmission scheme.

1. Introduction

State estimation has been an attractive subject in the past several decades. It is able to be applied to a wide variety of fields including environmental and industrial monitoring, earth sensing, and health care, etc. [1]. The rapid development of modern control, communication, and networking technologies enables a new generation of wireless sensor networks. Compared with classical wired systems, wireless sensor networks have several characteristics; for example, they can reduce the wired cables for having the system be used easily and can withstand in harsh environmental conditions. Although wireless sensor networks have many advantages, they are still subject to some disadvantages such as when adding a wireless channel, it may incur many problems; this is because they are usually powered by batteries with limited capacity. Replacing old batteries that are running out of energy is a costly operation and may not even be possible [2]. On the other hand, wireless channels may vary due to changes in external environment; thus, time-varying channel capacity may influence overall dynamic system performance. Considering the low-power nature of the sensors and the time-varying characteristic of wireless channels, the energy consumed by the sensors can be conserved by reducing the number of communication actions between sensors and estimators, but it may lower the estimation accuracy at the same time. Hence, taking estimation accuracy and energy conservation into account is essential for a data transmission strategy.

Most of the existing state estimation strategies adopt the approach to periodical transmission of information; however, it may consume more network bandwidth than necessary [3–5]. The idea of controlling number of data-transmission actions so as to achieve a trade-off between energy efficiency and estimation performance, which is usually referred to as controlled transmission times, has recently received a great deal of attention. For instance, a robust filter for discrete-time uncertain systems with both measurement-based aperiodic transmission and signal quantization is designed in [6]. Literature [7] studies the maximum likelihood estimation for a level-based data transmission scheme where the upper and lower bounds of communication rates are evaluated. Optimal and suboptimal consensus filters with intermittent communication protocols are derived in [8], where the stability on noise-free error dynamics of suboptimal filter is analyzed, and the corresponding estimated values-based transmission mechanism is constructed. The variance-based transmission conditions for scalar linear systems are considered in [9] and the asymptotic convergence properties of the iteration of the prediction variance are proved. A similar study for vector systems is presented and analyzed in [10] with the assumption that the communication channel is unreliable (i.e., each transmitted packets could be dropped by the network with a certain probability). A probabilistic transmission strategy is considered in [11]; its feature is that the number between consecutive transmission actions is a random variable governed by a finite-state Markov chain. In addition to the aforementioned controlled transmission strategies, the coding and quantization technology for controlling the communication burden in terms of shortening the packet lengths is an interesting alternative for energy-efficient sensor schedulers.

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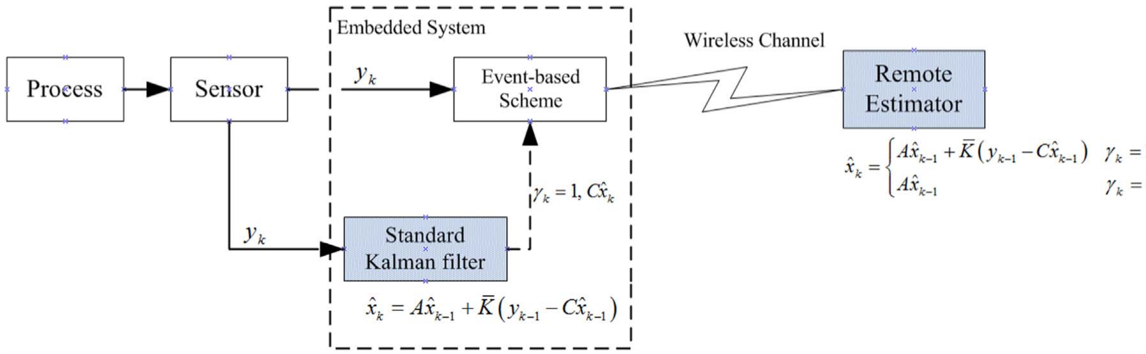

Fig. 1. An event-based sensor transmission scheme for remote state estimation.

Some research efforts on using such a technology are presented in what follows. The problem of minimum data rates for obtaining bounded mean-squared error in stochastic systems over certain probability packet-dropping links is investigated in [12]. The dynamic energy control and coding for state estimation in wireless sensors using predictive control is studied in [13] which achieves a tradeoff between energy consumption and estimation accuracy. Moreover, [14] presents a joint design of an adaptive quantization scheme and a recursive parameter estimator. Strong consistency, asymptotic unbiasedness, and normality are rigorously proved. Relays are employed to improve performance of Kalman filtering over wireless fading channels in [15]. Then, the relays are further utilized to perform a network-coding operation and the energy conservation can be achieved.

As for at what time a sensor should transmit data, many policies have been proposed in aforementioned literature. These transmission policies often lead to energy saving. However, the motivation of using these polities is usually heuristic. Normally, a threshold plays a key role in tuning parameters for obtaining a satisfactory tradeoff between estimation performance and number of transmitting actions. Compared with the existing results about these transmission strategies (e.g. [16] and [17]), how to theoretically select a policy has barely been reported in these literature. Furthermore, the assumption, where all the transmitted data received at the remote estimators, can be found in existing event-based estimation (e.g. [7] and [9]). The stability of the mean square for the remote estimation with packet dropouts is neglected in these studies.

In this paper, we consider the issue of state estimation based on the measurements taken by a battery-powered sensor. The remote estimator will receive the measurements through a wireless channel. It is assumed that the transmission itself will consume more energy than estimating computation, which is a reasonable assumption because the energy consumed by the transmission module is always much more than the computing module in practice; thus, an event-based strategy is adopted to reduce the number of sensor-to-estimator communication actions. The main contributions of this work include: an event-based decision rule is presented for linear stochastic systems. Compared with existing studies on event-based estimation, a more practical situation is assumed where data can experience random packet drops. The stability of the mean square for the remote estimator is proved.

Notations: $\mathbb{N}$ and $\mathbb{R}$ denote the sets of natural and real numbers, respectively; $\mathbb{R}^{m\times n}$ denotes the sets of m by n real-valued matrices, whereas $\mathbb{R}^n$ is short for $\mathbb{R}^{n\times 1}$; $\mathbb{R}_+^{n\times n}$ and $\mathbb{R}_{++}^{n\times n}$ are the sets of $n \times n$ positive semi-definite and positive definite matrices, respectively. When $X \in \mathbb{R}_+^{n\times n}$, we simply write $X \geq 0$ $\left(\text{or } X > 0 \text{ if } X \in \mathbb{R}_{++}^{n\times n}\right)$. For $X \in \mathbb{R}^{m\times n}$, X^{T} denotes the transpose of X and $\mathbb{E}[\cdot]$ denotes the mathematical expectation.

2. Problem statement

Consider the following stochastic linear time-invariant process:

$$\begin{aligned} x_{k+1} &= Ax_k + w_k \\ y_k &= Cx_k + v_k \end{aligned} \tag{1}$$

where k is the discrete time index, $x_k \in \mathbb{R}^n$ is the state vector, and $y_k \in \mathbb{R}^m$ is the sensor measurement. It is assumed that the constant matrices A and C are known. The noise process $\{w_k\}$, $\{v_k\}$, and the initial state x_0 are assumed mutually independent, white, zero-mean and have known variance $Q_w > 0$, $R > 0$ and $P_0 > 0$, respectively.

Moreover, the pair (C, A) is assumed to be observable and $\left(A, \sqrt{Q_w}\right)$ is controllable. After y_k is measured, an event in terms of a decision variable will decide to send it to the remote estimator or not. Let γ_k be the decision variable: if $\gamma_k = 1$, y_k will be sent and if $\gamma_k = 0$, it will not be sent. Hence, only when $\gamma_k = 1$, the estimator can know the exact values of y_k.

Fig. 1 is a block diagram describing the architecture of the data transmission. When an event occurs, i.e., $\gamma_k = 1$ for all k, the Kalman filter will provide $C\hat{x}_k$ to the event-based scheduler. When $\gamma_k = 0$, a simple prediction $A\hat{x}_{k-1}$ is needed for the scheduler. This needs few lines of programming codes in an embedded system and therefore it will by no means cause too much additional computing burden. Moreover, since long-term monitoring is considered in this paper, we employ a steady-state Kalman filter at the sensor side. This will also reduce the computing burden in the embedded system to some degrees. We designate $\bar{P}$ as the steady-state error covariance. When $\gamma_k = 1$ for all k, the estimated state values $\hat{x}_k$ by a steady-state Kalman filter at the remote estimator is recursively computed as follows

$$\hat{x}_{k+1} = A\hat{x}_k + \bar{K}\left(y_k - C\hat{x}_k\right), \tag{2}$$

where the steady-state Kalman filter gain $\bar{K}$ can be calculated as follows

$$\bar{K} = A\bar{P}C^T(C\bar{P}C^T + R_v)^{-1}, \tag{3}$$

and the steady-state error covariance $\bar{P}$ is computed via the following algebraic Riccati equation