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Brief paper

Dynamic sensor transmission power scheduling for remote state estimation ☆

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ABSTRACT

In this paper, we consider the problem of sensor transmission power scheduling for remote state estimation. We assume that the sensor has two transmission energy levels, where the high level corresponds to a high packet reception ratio. By exploiting the feedback information from the remote estimator, we aim to find an optimal transmission power schedule. We formulate the problem as a Markov decision process, and analytically develop a simple and optimal dynamic schedule which minimizes the average estimation error under the energy constraint. Furthermore, we derive the necessary and sufficient condition under which the remote state estimator is stable. It is shown that the estimation stability only depends on the high-energy packet reception ratio and the spectral radius of the system dynamic matrix.

1. Introduction

Networked control systems (NCSs) have attracted great research interest in the past decade, which have a broad range of applications including autonomous vehicles, environmental monitoring, industrial automation, smart grid, etc., (Hespanha, Naghshtabrizi, and Yonggang (2007)). In all these applications, state estimation is an indispensable ingredient. In this paper, we consider the scenario where a sensor is monitoring a system and transmits its local estimation data to a remote state estimator via a wireless communication network.

We assume the sensor has two transmission power levels, and the higher one corresponds to a lower data packet drop rate. To save energy usage (or equivalently to increase lifetime), the sensor tends to use lower transmission power as much as possible. This, however, introduces a large number of data packet drops which in turn deteriorate the estimation quality at the remote estimator. Therefore, when there is a constraint on the sensor energy usage, it is of great importance to optimally schedule the transmission power levels so as to minimize the estimation error at the remote estimator.

We also consider in this scenario that the remote estimator is able to send an acknowledgment packet back (which can be for example achieved by the media access control (MAC) protocol (Tanenbaum (2002))) to the sensor which indicates whether the transmitted packet is received or not. Under this feedback mechanism, the sensor is aware of the packet receptions in the previous times.

Before we present our main contributions and our approach for tackling the power scheduling problem, we briefly go over some related works in the literature. More references can be found from the references therein.

In Baras and Bensoussan (1988), they considered the optimal selection of a schedule of sensors, so as to optimally estimate a function of an underlying parameter. For a number of sensors and actuators, Walsh and Hong (2001) and Walsh, Hong, and Bushnell (2002) investigated when to schedule which process to access the network so that each process can remain absolutely stable. Gupta, Chung, Hassibi, and Murray (2006) proposed a stochastic sensor schedule and gave an optimal probability distribution over the sensors which minimizes an upper bound of the expected estimation

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errors. Sandberg, Rabi, Skoglund, and Johansson (2008) considered a heterogeneous sensor network, i.e., low-quality measurement with small cost and high-quality measurement with high cost, and proposed an optimal schedule using time-periodic Kalman filter. Similar problems of sensor scheduling were also considered in Arai, Iwatani, and Hashimoto (2008) and Arai, Iwatani, and Hashimoto (2009). Savage and La Scala (2009) considered an optimal sensor scheduling that minimizes the terminal estimation error covariance for scalar systems. Cao, Chen, Zhang, and Sun (2008) proposed a micro-environmental monitoring and data processing system based on wireless sensor network. In Cao, Cheng, Chen, and Sun (2013), they considered a networked cyber–physical system and developed a joint optimization framework, which consists of communication protocol and online control. Ren, Cheng, Chen, Shi, and Sun (2013) considered an optimal periodic sensor scheduling that minimizes the average estimation error covariance.

Walrand and Varaiya (1983) showed that feedback information is helpful in encoder–decoder design. Bansal and Başar (1989) proposed a simultaneous design of measurement and control strategies for ARMA models. Lipsa and Martins (2011) considered the joint design of pre-processor and estimator, to minimize an objective that combines the expected squared state estimation error and communication cost. They showed that threshold policies at the pre-processor and the estimator are jointly optimal. Both the problems in Walrand and Varaiya (1983) and Lipsa and Martins (2011) are analyzed in the finite time horizon. The most related work to this paper is Shi, Cheng, and Chen (2011), which considered a scheduling problem with two transmission power levels, where high level corresponds to perfect communication (i.e., the packet drop rate is 0) and low level introduces random packet drops. Compared with Shi et al. (2011), we have the following major differences.

1. We aim to find an optimal schedule among the entire schedule space, while Shi et al. (2011) only analyzed periodic schedules.
2. The tools used in this paper is different, which utilizes the communication feedback to improve the remote estimation quality.
3. Each transmission energy level introduces a packet drop rate, which is more realistic, while a higher transmission level leads to perfect communication in Shi et al. (2011).
4. Since the transmitted data can be randomly dropped and is never guaranteed to arrive under any transmission power level, the state estimation error at the remote estimator side may diverge. Thus it is necessary to analyze the stability condition, which is not an issue in Shi et al. (2011).

The main contributions of this paper are summarized as follows.

1. We show how online information can be exploited to minimize the average expected estimation error covariance by an energy-constrained sensor. The problem is formulated as a Markov decision process.
2. We develop a simple and optimal scheduling scheme, and derive an analytical expression of the minimum expected average estimation error covariance.
3. We derive a sufficient and necessary condition under which the stability of the estimator is guaranteed.

The remainder of this paper is organized as follows. In Section 2, we introduce the system models and problem formulation. In Section 3, we give some notations and some preliminaries on Kalman filter. Section 4 shows that we only need to consider stationary schedules. The optimal sensor scheduling scheme with a simple structure is derived in Section 5. Section 6 provides the sufficient and necessary condition for the estimator's stability. Two examples are provided in Section 7 to demonstrate the results. Conclusion is given at the end.

Notations. $\mathbb{Z}$ is the set of integers. $\mathbb{Z}^+$ is the set of positive integers; $k \in \mathbb{Z}^+$ is the time index. $\mathbb{N}$ is the set of nonnegative integers.

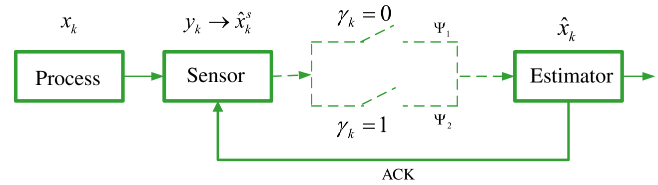

Fig. 1. System block diagram.

$\mathbb{R}^n$ is the n-dimensional Euclidean space. $\mathbf{0}_n$ is an $1 \times n$ row vector $(0, 0, \ldots, 0)$. $\mathbb{S}_+^n$ is the set of $n \times n$ positive semi-definite matrices. We simply write $X \geq 0$, when $X \in \mathbb{S}_+^n$; and write $X > 0$, when X is positive definite. For functions f, f_1, f_2: $\mathbb{S}_+^n \to \mathbb{S}_+^n$, $f_1 \circ f_2$ is defined as $f_1 \circ f_2 \triangleq f_1(f_2(X))$, and f^t is defined as $f^t(X) \triangleq \underbrace{f \circ f \circ \cdots \circ f}_{t \text{ times}}(X)$ (particularly, $f^0(X) = X$).

2. System models and problem definition

2.1. System models

Consider the following dynamical model

$$x_{k+1} = Ax_k + \omega_k, \qquad y_k = Cx_k + \nu_k,$$

where $x_k \in \mathbb{R}^n$ is the state of system, $y_k \in \mathbb{R}^m$ is the measurement obtained by the sensor, and A, C are known time-invariant real matrices. $\omega_k \in \mathbb{R}^n$ and $\nu_k \in \mathbb{R}^m$ are both zero-mean Gaussian random noises with covariances $\mathbb{E}[\omega_k \omega_j'] = \Delta_{kj} Q$, $Q \geq 0$, $\mathbb{E}[\nu_k \nu_j'] = \Delta_{kj} R$, $R > 0$, and $\mathbb{E}[\omega_k \nu_j'] = 0\, \forall j, k$, where $\Delta_{kj} = 0$ if $k \neq j$ and $\Delta_{kj} = 1$ otherwise. The initial state x_0 is also a zero-mean Gaussian random vector which is uncorrelated with ω_k or ν_k and has covariance $P_0 \geq 0$. Assume the pair $(A, \sqrt{Q})$ is controllable and (C, A) is observable.

Let $Y_k = \{y_1, \ldots, y_k\}$ be all the measurement data of the system collected by the sensor from time 1 to time k. Based on Y_k, the sensor is able to estimate the system's state as $\hat{x}_k^s$ which is given by

$$\hat{x}_k^s = \mathbb{E}[x_k | Y_k], \qquad P_k^s = \mathbb{E}[(x_k - \hat{x}_k^s)(x_k - \hat{x}_k^s)' | Y_k],$$

where P_k^s is the corresponding estimation error covariance. We assume that the sensor has two energy levels to transmit $\hat{x}_k^s$ to the remote estimator (see Fig. 1). When the sensor uses a low energy Ψ_1 at time k, the data packet can be successfully delivered to the remote estimator with probability (w.p.) $p_1 \in [0, 1)$; when the sensor uses a high energy $\Psi_2 (\Psi_2 > \Psi_1 > 0)$, the data packet can be successfully delivered w.p. $p_2 \in (0, 1]$. From Zuniga and Krishnamachari (2004), the reception rate under transmission power P_t can be approximated by

$$p = \left(1 - \frac{1}{2} exp^{-\frac{P_t - PL - P_n}{2} \frac{1}{0.64}}\right)^{8f}.$$

We can see p is increasing in P_t. Thus it is reasonable to assume $p_2 > p_1$. At time k, sensor will choose one power level to transmit the packet. Let $\gamma_k = 0$ or 1 be the sensor's decision variable at time k whether it chooses the low level or high level to send its current data packet. We use θ to denote sensor's scheduling scheme that assigns the value of γ_k at each k.

In this paper, we assume there is a *communication feedback* between the sensor and the remote estimator (see Fig. 1): when a packet containing $\hat{x}_k^s$ has been transmitted by the sensor, the sensor will be know that whether this packet is successfully received by the estimator after time k. This communication feedback can be achieved by the media access control (MAC) data communication protocol (Rossi, Badia, & Zorzi, 2006; Tanenbaum, 2002). For example, in the popular used CSMA/CA protocol, receiver will send a short acknowledgment frame (ACK) back to the transmitter to signify the receipt. If the sender does not receive an ACK frame, it indicates that the transmission was unsuccessful.