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Brief paper

Sensor data scheduling for optimal state estimation with communication energy constraint☆

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ABSTRACT

In this paper, we consider sensor data scheduling with communication energy constraint. A sensor has to decide whether to send its data to a remote estimator or not due to the limited available communication energy. We construct effective sensor data scheduling schemes that minimize the estimation error and satisfy the energy constraint. Two scenarios are studied: the sensor has sufficient computation capability and the sensor has limited computation capability. For the first scenario, we are able to construct the optimal scheduling scheme. For the second scenario, we are able to provide lower and upper bounds of the minimum error and construct a scheduling scheme whose estimation error falls within the bounds.

1. Introduction

Networked sensing and control systems have gained much interest in the past decade (Hespanha, Naghshtabrizi, & Xu, 2007). Applications of networked sensing and control systems are found in a growing number of areas, including autonomous vehicles, environment and habitat monitoring, industrial automation, transportation, etc.

In some networked sensing applications, sensors are battery-powered, hence only limited energy is available for data collection and transmission. Consequently a sensor cannot transmit its measurement data at all times due to the energy constraint, and it has to decide whether to send its current data packet or not. This decision-making process is referred to as *sensor data scheduling*.

On one extreme, sending no data consumes no energy. However, without receiving and processing the sensor measurement data, the estimation error of the underlying parameters may grow rapidly which is undesirable in situations such as target tracking and rescue and surveillance. On the other extreme, sending data at all times assures that the estimation error is a minimum but at the price of high energy cost. The latter case may not even be feasible due to the energy constraint. Thus proper schedule of the sensor data transmission is needed such that the energy constraint is satisfied and the estimation error is kept as small as possible. Constructing such a proper sensor data scheduling scheme is the focus of this paper.

Sensor scheduling has been a hot topic of research for many years. Different formulations and approaches have been proposed. Baras and Bensoussan (1988) studied nonlinear state estimation problem and considered scheduling a set of sensors so as to optimally estimate a function of an underlying parameter. Walsh and Ye (2001) and Walsh, Ye, and Bushnell (2002) studied the problem of when to schedule which process to access to the network so that all processes remain stable. Gupta, Chung, Hassibi, and Murray (2006) considered a different scheduling problem where there is one process and multiple sensors. They proposed a stochastic sensor scheduling scheme and provided the optimal probability distribution over the sensors to be selected. Tiwari, Jun, Jeffcoat, and Murray (2005) studied the problem of sensor scheduling for discrete-time state estimation using a Kalman filter. They considered two processes and one sensor and proposed schemes to determine which process that the sensor needs to observe in order to minimize the total estimation error. Shi, Epstein, Sinopoli, and Murray (2007) combined the ideas from Gupta et al. (2006) and Tiwari et al. (2005) and proposed two novel scheduling schemes in a sensor network by employing feedback from the estimator to the sensors. Hovareshti, Gupta, and Baras (2007) considered sensor scheduling using smart sensors, i.e., sensors with some memory and processing capabilities, and demonstrated that estimation

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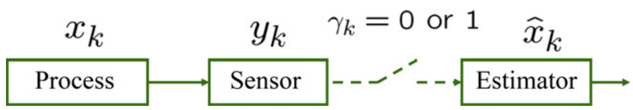

Fig. 1. System block diagram.

performance can be improved. Sandberg, Rabi, Skoglund, and Johansson (2008) considered estimation over a heterogeneous sensor network. Two types of sensors were investigated: the first type has low-quality measurement but small processing delay, while the second type has high-quality measurement but large processing delay. Using a time-periodic Kalman filter, they showed how to find an optimal schedule of the sensor communication. Similar work has been done by Arai, Iwatani, and Hashimoto (2008, 2009) where fast sensor scheduling was proposed for networked sensor systems. Savage and Scala (2009) considered the problem of optimal sensor scheduling for scalar systems that minimizes the terminal error.

The main contributions of this paper and comparison with existing work from the literature are summarized as follows.

(1) We develop sensor scheduling schemes that provide the best estimation quality subject to sensor energy constraint. To the best of our knowledge, the problem formulation is novel.
(2) We focus on scheduling of the sensor measurement data, while most of the existing work focused on scheduling of a set of (heterogeneous) sensors.
(3) Since the solution space contains infinite scheduling schemes which are discrete in nature, most existing work proposed algorithms that typically generate a suboptimal schedule, and nothing in general is said on the optimality of the proposed schedule. However, in this paper, when the sensor has sufficient computation capability, we are able to construct an optimal scheduling scheme; when the sensor has limited computation capability, we are able to provide a lower and upper bound of the estimation error for the optimal scheme.

The remaining of the paper is organized as follows. In Section 2, we introduce the system models and problem setup. In Section 3, we define some frequently used notations and provide some preliminaries on the Kalman filter. In Section 4, we provide the necessary condition for optimal scheduling schemes. In Section 5, we study the scenario when the sensor has sufficient computation and present an optimal scheduling scheme. In Section 6, we study the scenario when the sensor has limited computation and present a suboptimal schedule. Concluding remarks are given in the end.

Notations. $\mathbb{Z}$ is the set of non-negative integers. k is the time index. $\mathbb{N}$ is the set of natural numbers. $\mathbb{R}^n$ in n-dimensional Euclidian space. $\mathbb{S}^n_+$ is the set of n by n positive semi-definite matrices. When $X \in \mathbb{S}^n_+$, we simply write $X \geq 0$; when X is positive definite, we write $X > 0$. For functions $f, f_1, f_2 : \mathbb{S}^n_+ \to \mathbb{S}^n_+$, $f_1 \circ f_2$ is defined as $f_1 \circ f_2(X) \triangleq f_1(f_2(X))$ and f^t is defined as $f^t(X) \triangleq \underbrace{f \circ f \circ \cdots \circ f}_{t \text{ times}}(X)$.

2. Problem setup

2.1. System models

Consider the following discrete linear time-invariant system (Fig. 1)

$$x_{k+1} = Ax_k + w_k, \quad (1)$$

$$y_k = Cx_k + v_k. \quad (2)$$

In the above equations, $x_k \in \mathbb{R}^n$ represents the current state of the process, $y_k \in \mathbb{R}^m$ is the measurement data taken by the sensor at time k, $w_k \in \mathbb{R}^n$ and $v_k \in \mathbb{R}^m$ are zero-mean Gaussian random noises with covariances $\mathbb{E}[w_k w_j'] = \delta_{kj} Q \geq 0$, $\mathbb{E}[v_k v_j'] = \delta_{kj} R > 0$, $\mathbb{E}[w_k v_j'] = 0$ $\forall j, k$, 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 that is uncorrelated with w_k or v_k and has covariance $\Pi_0 \geq 0$. Further assume that $(A, \sqrt{Q})$ is controllable and (C, A) is observable.

Assume that the sensor communicates its data packet with a remote estimator via a network. Let

$$Y_k = \{y_1, \ldots, y_k\} \quad (3)$$

be all the measurements collected by the sensor from time 1 to k. The sensor's local state estimate $\hat{x}_k^s$ and its corresponding error covariance P_k^s are calculated as

$$\hat{x}_k^s = \mathbb{E}[x_k | Y_k], \quad (4)$$

$$P_k^s = \mathbb{E}[(x_k - x_k^s)\,(x_k - x_k^s)' | Y_k]. \quad (5)$$

Most commercially available sensor nodes nowadays have different transmission power levels (Xiao, Cui, Luo, & Goldsmith, 2006). Reliable data flow is typically achieved using high power transmission. Low power transmission may cause unreliable data flow and data packet drops are typical consequences. For simplicity, we assume the sensor operates in two energy levels. When the sensor uses a high energy Δ at time k, the data packet can be successfully delivered to the remote estimator; when the sensor uses a low energy δ, the data packet can be successfully delivered only with probability $\lambda \in (0, 1)$. We assume both Δ and δ are rational numbers. When δ energy is used, let $\lambda_k = 1$ or 0 be the indicator function whether the data packet arrives at the estimator successfully or not. Assume λ_k's are i.i.d Bernoulli random variables and $\mathbb{E}[\lambda_k] = \lambda$.

Let $\gamma_k = 1$ or 0 be the sensor's decision variable at time k whether it should send its current data packet using Δ or δ energy. Let θ denote a scheduling scheme that defines the value of γ_k at each k. Clearly the set of all scheduling schemes consists of 2^k different schemes up to time k, most of which are unstructured and are intractable to analyze. We thus focus on the subset of all periodic scheduling schemes which we denote as Θ.

Denote $D_k(\theta)$ as the set of all data packets received by the estimator up to time k. In general $D_k(\theta)$ could be different from Y_k defined in Eq. (3) due to the possible data packet drops. Similar to calculating $\hat{x}_k^s$ and P_k^s, for a given θ, the state estimate $\hat{x}_k(\theta)$ and its associated error covariance $P_k(\theta)$ at the remote state estimator are calculated as

$$\hat{x}_k(\theta) = \mathbb{E}[x_k | D_k(\theta)], \quad (6)$$

$$P_k(\theta) = \mathbb{E}[(x_k - \hat{x}_k)(x_k - \hat{x}_k)' | D_k(\theta)]. \quad (7)$$

For simplicity, we shall write $\hat{x}_k(\theta)$ as $\hat{x}_k$, etc., when the underlying scheduling scheme θ is clear from the context.

2.2. Problems of interest

For a given θ, define $J(\theta)$ as the average energy cost associated with it, i.e.,

$$J(\theta) \triangleq \lim_{N\to\infty} \frac{1}{N} \sum_{k=1}^{N} (\gamma_k \Delta + (1 - \gamma_k)\delta), \quad (8)$$

and $P_a(\theta)$ as the average expected estimation error covariance, i.e.,

$$P_a(\theta) \triangleq \lim_{N\to\infty} \frac{1}{N} \sum_{k=1}^{N} \mathbb{E}[P_k]. \quad (9)$$

Let Ψ be a given energy budget. Assume that Ψ is a rational number and $\delta \leq \Psi \leq \Delta$.

In this paper, we are interested in finding a periodic scheduling scheme θ that solves the following optimization problem.