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Optimal sensor scheduling for two linear dynamical systems under limited resources in sensor networks

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ABSTRACT

In this paper, we aim to design the optimal transmission scheme for two Gauss–Markov systems with finite resources. The setup that only two sensor nodes were scheduled, which monitor different linear dynamical systems, respectively. Two scenarios : the sensor has abundant calculation capability and the sensor has limited calculation capability are considered. For the second scenario, considering that the optimal schedule should collected a finite sequence of previous measurements. We are able to construct a quasi-optimal schedules. Due to bandwidth limitation and transmission power restriction, the sensors cannot communicate with the remote center and send the measurement data all the times. By exploiting the estimation error covariance at the remote estimation center to describe the quality of communication, the transmission schedule problem is formulated as an optimal problem. A necessary condition for the scheduling scheme of the sensors to be optimal is provided. Based on this necessary condition, we propose an explicit optimal periodic schedule, which is rigorously proved to have a minimal estimation error at the estimation center while satisfying the transmission power and channel bandwidth constraints. Simulation examples are given at last to verify the validity of the theoretical results.

1. Introduction

Networked control systems (NCSs) have gained increasing investigation attention over the last decade [1,2]. Owing to the advances in wireless communication, control and sensor technologies, NCSs have extensive applications to the fields such as unmanned aerial vehicle, battlefield surveillance, environmental monitoring, smart grid [3,4], health care and aerospace. Specifically, in recent years, networked control system theory has been successfully applied to wireless sensor networks and fruitful results are obtained [5]. Remote state estimation plays an very important role in the above applications. Many techniques, for instance, Kalman filter, are developed to estimate the system state optimally by iteration when receiving the observed data with inevitable noise [7,9]. With the development of internet, network sensing and network control promote the system convenience of operation and diagnosis, while keeping and enhancing the agility and flexibility of the system. Nevertheless, despite of many advantages the networked control system provide, there are also some obstacles which limit the application and development of results on networked control system. For instance, the finite shared channel bandwidth of system may impede information transmission of nodes in NCSs which in some degree reduces the quality of estimation [10]. Besides, in general, the sensor nodes in a NCS (e.g., wireless sensor network) are powered by batteries which have limited power and are hard to charge or replace [6]. Hence, sensors can only communicate with each other in limited times for data collection. Accordingly, a sensor has to decide whether to send its current data packet or not. This decision-making process is referred to as sensor data scheduling [15]. There are large numbers of literatures focusing on the investigation on sensor data scheduling [3]. Different methods are proposed to solve the sensor scheduling problems with different scheduling objectives, e.g., [13,15]. Some related works are curtly reviewed as follows. Tiwari et al. [11] consider sensor scheduling problem for discrete-time system which adopts Kalman filter to obtain the estimation of system state. They study the case that there are two system processes and only a single sensor need to observe the above two system states, respectively. The single sensor only observes one process at a time; thus, for the sake of minimizing the sum of two system estimation errors, they propose a scheduling scheme to decide which process that the sensor behooves observe for raising the total system performances. Shi et al. [13] study the scenario that there are two sensors scheduling a process. As a result of the channel bandwidth constraint, only one sensor is permitted to observe the process at

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a time. Considering that the two sensors have different level observation accuracies, the optimal periodic scheduling scheme determining which sensor need to observe the process is proposed to minimize the system average estimation error covariance. Yang et al. [14] consider sensor selection in order to reach consensus over wireless sensor networks under limited energy constraint. They provide a sensor selection scheme to schedule sensors to measure the system state in order to minimize the system estimation error covariance while guarantees the sensor energy constraint satisfied. Shi et al. [15] also ponder sensor scheduling problem under transmission power constraint and provide an optimal sensor scheduling scheme including energy plan that aims at minimizing the estimation error covariance meanwhile ensuring the energy constraint satisfied.

The aforementioned literatures are devoted to a single system [16,18] or process [19] under single constraint [10,20,21] such as energy or bandwidth [22]. Ding et al. [12] are concerned with the attack scheduling of deception attacks for discrete time systems, an attacker with the given attack task needs to decide how many the maximum number is for different kinds of attack scenarios. However, in most real applications, sensors are sparsely placed to monitor multiple dynamical processes of interest [8]. Hence, it is of both theoretical and practical interest to consider sensor scheduling for multiple systems. In addition, as pointed out previously, we may encounter essential restrictions on communication and power in practical applications simultaneously. In view of the above inspiration, in this manuscript, we aim to design the optimal transmission scheme for two Gauss–Markov systems with finite resources. Considering that two sensors monitor two different systems, respectively, only one sensor is allowed to monitor a single system and send the communication data by channel at a time due to limited communication bandwidth. Moreover, we devote ourself to scheduling two separate processes while satisfying channel bandwidth and transmission power constraint. The main contributions of this work are summarized as follows:

1. We consider and analyse two scenarios: the sensor has abundant calculation capability and the sensor has limited calculation capability in this manuscript. For the first scenario, we are able to construct the optimal scheduling scheme. For the second scenario, we are able to provide the optimal scheduling scheme based on Kalman filtering with intermittent observation when the sensor is scheduled to send current and several previous $S+p$ measurements, providing the estimator error covariance has an upper bound whenever a measurement packet arrives. When the window of size $T=\infty$, we get some great theoretical results and provide the optimal scheduling scheme when all the measurement data packets so far are transmitted to remote estimator. The obtained estimation error covariance is a lower bound of other case. Besides, we show that the same schedule scheme is still optimal as long as T is sufficiently large and the lower bound of T is relevant to the energy budget.
2. Most existing works focus on a single system or process under single constraint such as limited energy or bandwidth, not enough research efforts have been put in the case of different sensors monitoring different systems, which is widely encountered in practice. Typically in most real applications, sensors are sparsely placed to monitor multiple dynamical processes of interest under multiple restrictions. Thus, In view of the above inspiration, we focus on scheduling two sensors observing two systems while considering limited energy and bandwidth constraints simultaneously.

The remainder of the paper is organized as follows. In Section 2, the problem of interest is formulated and some preliminary results are provided. Section 3 gives a necessary condition for the sensor scheduling scheme to be optimal. Based on such necessary condition, Section 4 constructs a specific optimal scheduling scheme. An example is provided in Section 5 to verify the optimality of scheduling scheme. Conclusions are drawn at last in Section 6.

Notations: Z denotes the set of non-negative integers. k represents the time index. N denotes the set of natural numbers. R^n is n-dimensional Euclidian spaces. S^n_+ and S^n_{++} represent the sets of $n\times n$ positive semi-definite and positive definite matrices, respectively. If $X\in S^n_+$, we simply depict as $X\geq 0$ and $X>0$ if $X\in S^n_{++}$. For a matrix X, X' denotes its transpose. $Tr[\cdot]$ represents the trace of a matrix. $X\geq Y$ if $X-Y\in S^n_+$. $E[\cdot]$ denotes the expectation of a random variable. For function f_1, f_2 with appropriate domains, $f_1f_2(x)$ denotes the function composition $f_1(f_2(x))$, and $f^n(x)\triangleq f(f^{n-1}(x))$ with $f^0\triangleq x$.

2. Problem setup

2.1. System model

We consider the two Gauss–Markov discrete-time systems as follows (see Fig. 1):

$$x^i_{k+1}=A_ix^i_k+w^i_k,\ i=1,2, \tag{1}$$

where $x^i_k\in R^n$ represents state vector of system i at time k. There are also two sensors that are used to observe these two systems, respectively,

$$y^i_k=C_ix^i_k+v^i_k,\ i=1,2, \tag{2}$$

y^i_k is the sensor measurement of system i, $w^i_k\in R^n$ and v^i_k are reciprocally unrelated White Gaussian Noises (WGN) with covariances $Q_i\geq 0$ and $R_i>0$ for $i=1,2$. The initial status value x^i_0 is also zero mean Gaussian and its covariance matrix is $E[x^i_0x^i_0{}']=\Pi_i>0$, which is unrelated with w^i_k and v^i_k for all time $k\geq 0$ and $i=1,2$. (A_i, C_i) and $(A_i,\sqrt{Q_i})$ are observable and controllable for $i=1,2$, respectively.

After sensor i obtains y^i_k, we describe the information set of sensor i at time k by

$$\zeta^i_k\triangleq\{\gamma^i_0,\gamma^i_1,\dots,\gamma^i_k,\gamma^i_0y^i_0,\gamma^i_1y^i_1,\dots,\gamma^i_ky^i_k\}, \tag{3}$$

with $\zeta^i_{-1}\triangleq\emptyset$ for $i=1,2$. Denote by $\hat{x}^s_{k,i}=E[x^i_k|\zeta^i_k]$ which is the minimum mean squared error estimation of x^i_k. Define the local estimation error of sensor i as

$$e^i_k=x^i_k-\hat{x}^s_{k,i}. \tag{4}$$

We also define $\hat{x}^i_{k|k-1}\triangleq E[x^i_k|\zeta^i_{k-1}]$ as *a priori* evaluate of x^i_k, which is the predicted state of system when the observation value is unknown and $P^i_{k|k-1}\triangleq E[(x^i-x^i_{k|k-1})(x^i-x^i_{k|k-1})'|\zeta^i_{k-1}]$ as the evaluate error covariance matrices of $\hat{x}^i_{k|k-1}$. From standard Kalman filtering [23], $\hat{x}^s_{k,i}$ and its estimation error covariance matrix $P^s_{k,i}=E[(e^i_k)(e^i_k)'|\zeta^i_k]$ is obtained by iteration as follows:

$$\hat{x}^i_{k|k-1}=A_i\hat{x}^s_{k-1,i}, \tag{5}$$

$$P^i_{k|k-1}=A_iP^s_{k-1,i}A_i'+Q_i, \tag{6}$$

$$K_i=P^i_{k|k-1}C_i'[C_iP^i_{k|k-1}C_i'+R_i]^{-1}, \tag{7}$$

$$\hat{x}^s_{k,i}=\hat{x}^i_{k|k-1}+K_i[y^i_k-C_i\hat{x}^i_{k|k-1}], \tag{8}$$

$$P^s_{k,i}=[I-K_iC_i]P^i_{k|k-1}, \tag{9}$$

where the recursion starts from $\hat{x}^s_{0,i}=0$ and $P^s_{0,i}=\Pi_0$ for each $i=1,2$. Two scenarios are considered in this paper described in the following subsection.