



Optimal scheduling of multiple sensors over shared channels with packet transmission constraint[☆]

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ABSTRACT

In this work, we consider the optimal sensory data scheduling of multiple process. A remote estimator is deployed to monitor S independent linear time-invariant processes. Each process is measured by a sensor, which is capable of computing a local estimate and sending its local state estimate wrapped up in packets to the remote estimator. The lengths of the packets are different due to different dynamics of each process. Consequently, it takes different time durations for the sensors to send the local estimates. In addition, only a portion of all the sensors are allowed to transmit at each time due to bandwidth limitation. We are interested in minimizing the sum of the average estimation error covariance of each process at the remote estimator under such packet transmission and bandwidth constraints. We formulate the problem as an average cost Markov decision process (MDP) over an infinite horizon. We first study the special case when $S = 1$ and find that the optimal scheduling policy always aims to complete transmitting the current estimate. We also derive a sufficient condition for boundedness of the average remote estimation error. We then study the case for general S . We establish the existence of a deterministic and stationary policy for the optimal scheduling problem. We find that the optimal policy has a consistent property among the sensors and a switching type structure. A stochastic algorithm is designed to utilize the structure of the policy to reduce computation complexity. Numerical examples are provided to illustrate the theoretical results.

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1. Introduction

Networked control systems are control systems which incorporate communication systems. With the wireless communication technology, control systems can be remotely operated and set up in a distributed configuration. Applications of networked control systems are numerous, including industrial automation, habitat monitoring, smart grid and autonomous traffic management (Akyildiz, Su, Sankarasubramanian, & Cayirci, 2002). A salient feature of the networked controls systems is that the control signal and sensory data are transmitted via packets through a communication network. Although the wireless communication channel facilitates

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remote operation, algorithm design for the whole control system becomes more difficult as the communication channels have limited capacity to deliver information perfectly. The packets may be dropped, delayed, out-of-sequence, etc. (You & Xie, 2013; Zhang, Gao, & Kaynak, 2013).

As state estimation is crucial to feedback control systems, efficient processing of sensory data under limited resources is crucial. The accuracy of the state estimation can be improved by designing customized algorithms of sensory data scheduling. These algorithms tradeoff the estimation performance and constraints on the available resources, e.g., channel bandwidth, energy budget, etc. Shi, Cheng, and Chen (2011) proposed a periodic optimal sensory data scheduling policy for a single sensor under a limited energy budget. Other works on optimal allocation of energy for sensors can be found in Nourian, Leong, and Dey (2014) and Wu, Li, Quevedo, Lau, and Shi (2015) and references therein. To maximize lifetime of the network, Mo, Shi, Ambrosino, and Sinopoli (2009) provided a sensor selection algorithm based on convex optimization. As communication is expensive in wireless sensor network, efficient utilization of online information to reduce communication rate is another research focus. Event-triggered transmission strategies

were proposed to deal with this issue (Ding, Wang, Ho, & Wei, 2017; Ren, Wu, Johansson, Shi, & Shi, 2018; Shi, Chen, & Shi, 2014; Wu, Jia, Johansson, & Shi, 2013). The bandwidth of wireless communication channel can be limited, and only a few sensors are allowed to be activated in each time slot because the sensors can interfere with each other. Gupta, Chung, Hassibi, and Murray (2006) analyzed the performance of a stochastic sensor selection algorithm. Other researches related to the optimal scheduling of multiple sensors under channel bandwidth constraints can be found in Han, Wu, Zhang, and Shi (2017), Hovareshti, Gupta, and Baras (2007), Mo, Garone, and Sinopoli (2014), Ren, Wu, Dey, and Shi (2018) and Zhao, Zhang, Hu, Abate, and Tomlin (2014). Mo, Garone et al. (2014) and Zhao et al. (2014) proved that the optimal sensor scheduling scheme can be approximated arbitrarily by a periodic schedule over an infinite horizon. As the sensors are nowadays equipped with storage buffer and on-board computation unit, pre-processing can be done on the sensor. Hovareshti et al. (2007) showed that the estimation quality can be improved for such type of smart sensors. Han et al. (2017) proved that the optimal scheduling policy over an infinite horizon can also be arbitrarily approximated by a periodic schedule if smart sensors are used.

Many previous works assumed that it takes the same time duration for transmission of all packets and the transmissions are done in one time step. This is based on the assumption that the data packets have the same length. To improve control system performance by efficiently utilizing the communication resources, the packet length can be chosen to be different. Pioneering work was done in Tamboli and Manikopoulos (1995). Optimal allocation of packet length has been studied in wireless communication community, e.g., Dong et al. (2014). It was shown in Mori, Ishii, and Ogose (2011) that both latency and throughput performance of the communication channel can be improved. In some state-of-the-art communication protocols, e.g., Time Slotted Channel Hopping (TSCH, IEEE 802.15.4e), the packet length of different packets can be different and the data transmission scheme can be designed accordingly. Standards of TSCH application can be found in Watteyne, Palattella, and Grieco (2015). Besides the communication protocols, some applications, e.g., underwater vehicles, can only bear a few bits in one transmission (Cui, Kong, Gerla, & Zhou, 2006). In those cases, the local estimate should be split into more than one packet. Zhao, Kim, Shi, and Liu (2011) studied how to tradeoff the quality of control and the quality of service in the communication channel through optimal packet length allocation.

Different from previous works on sensory data scheduling, our work focuses on the constraint of packet length. We study the sensory data scheduling for remote state estimation of multiple linear time-invariant stochastic processes, each driven by white Gaussian noises. Every process is measured by a sensor, which is able to compute the local estimate of the process and send the local estimate to a remote estimator. Because the dynamics of different processes are different, the packet lengths of each process may be different. Consequently, it costs different time durations for each sensor to complete one transmission of an estimate. Moreover, not all the sensors can transmit data to the remote estimator at the same time step due to bandwidth limitations. We are interested in minimizing the average estimation error at the remote estimator over an infinite time horizon.

Some preliminary results have been reported in our conference paper (Wu, Ren, Dey, & Shi, 2017), in which we formulated the optimal scheduling of sensors under the packet length and bandwidth constraints as an infinite time horizon Markov decision process (MDP) with an average cost criteria. We proved that there exists a deterministic and stationary optimal policy for the MDP. Moreover, we showed that the optimal policy has nice properties, i.e., consistency and switching type structure. The consistency means that

once a sensor is chosen to schedule, the transmission of the current estimate should not be interrupted by selecting other sensors. The switching type structure stands that the policy on the state space is separated by curves (2-dimension) or hyperplanes (3-dimension or higher).

The problem considered in this work is challenging because scheduling multiple sensors monitoring multiple processes can be classified as a restless bandit problem, which is proven to be computationally intractable (Papadimitriou & Tsitsiklis, 1999). Moreover, as we consider the packet length constraint and lossy transmission, the state space of the MDP formulation is embedded in a high dimensional space. The analysis of the corresponding MDP is thus complex as well.

Compared with the conference paper, our novel contributions are as follows.

(1) Different from the perfect channel assumption in the conference paper, the problem formulation of this work includes the case when the communication channel is lossy. The erasure phenomenon can make the remote estimation error unbounded (e.g., Sinopoli et al. (2004)). Suppose a local estimate, which might consist of several packets has been selected to be transmitted. If the starting packet has been received by the remote estimator and the ending packet has not been received by the remote estimator, the estimate is defined as in-transmission. When a packet loss occurs, transmitting the most updated or the current in-transmission estimate is to be studied. In this work, we show that it is optimal to continue transmitting the current in-transmission estimate, which can be viewed as consistency within one process for the optimal policy.

(2) In our conference work, the proof of the existence of a deterministic and stationary policy applies only to the unstable processes in a perfect channel. In this work, we adopt another framework and establish the existence result by showing a set of conditions in Sennott (1996).

(3) We extend the results of switching policy to the lossy channel case. By utilizing the switching structure, we develop a stochastic numerical algorithm to compute the switching curve of the optimal policy. This reduces computation overhead compared with directly applying a value iteration algorithm to the original MDP problem.

The remainder of this paper is organized as follows. In Section 2, we provide the mathematical formulation of the problem of interest. The main results, which consist of the MDP formulation, the existence of a deterministic and stationary policy, the structure of the optimal policy, and a stochastic algorithm for computing the switching curve are given in Section 3. In Section 4, a numerical example is provided to illustrate the main results. We summarize the paper in Section 5.

Notation: Denote \mathbb{N} as the set of integers greater than zero. For a matrix X , let $\text{Tr}(X)$, X^\top and $\rho(X)$ represent the trace, the transpose and the spectral radius of X , respectively. The identity matrix is I , and its size is determined from the context. For a square matrix $X \in \mathbb{R}^{n \times n}$, $X \succ (\succeq) 0$ stands for X is positive (semi-)definite. Let $P(\cdot)$ and $P(\cdot|\cdot)$ stand for the probability and conditional probability, and $\mathbb{E}[\cdot]$ stands for the expectation of a random variable.

2. System setup and problem formulation

Consider the following S independent discrete-time linear time-invariant dynamic processes in Fig. 1:

$$x_{k+1}^{(i)} = A_i x_k^{(i)} + w_k^{(i)},$$

where $i \in N \triangleq \{1, \dots, S\}$, $x_k^{(i)} \in \mathbb{R}^{n_i}$ is the state of the i th process at time k , A_i is the system matrix, and $w_k^{(i)}$ is the state disturbance noises, which is Gaussian distributed with mean zero and covariance $Q_i \succeq 0$. The initial state $x_0^{(i)}$ is also a zero-mean

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