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Brief paper

Data-driven power control for state estimation: A Bayesian inference approach[☆]

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ABSTRACT

We consider sensor transmission power control for state estimation, using a Bayesian inference approach. A sensor node sends its local state estimate to a remote estimator over an unreliable wireless communication channel with random data packet drops. As related to packet dropout rate, transmission power is chosen by the sensor based on the relative importance of the local state estimate. The proposed power controller is proved to preserve Gaussianity of local estimate innovation, which enables us to obtain a closed-form solution of the expected state estimation error covariance. Comparisons with alternative non-data-driven controllers demonstrate performance improvement using our approach.

1. Introduction

Wireless networked systems have a wide spectrum of applications in smart grid, environment monitoring, intelligent transportation, etc. State estimation is a key enabling technology where the sensor(s) and the estimator communicate over a wireless network. Energy conservation is a crucial issue as most wireless sensors use on-board batteries which are difficult to replace and typically are expected to work for years without replacement. Thus power control becomes crucial. In this work, we consider sensor transmission power control for remote state estimation over a packet-dropping network. Transmission power control in state estimation scenario has been considered from different perspectives. Some works took transmission costs as constant. Shi and Xie (2012) assumed sensors to have two energy modes, allowing it to send data to a remote estimator over an unreliable channel either using a high or low transmission power level. The optimal power controller is to minimize the expected terminal estimation error at the remote estimator subject to an energy constraint. Similar works can also be found in Imer and Basar (2005) and Xu and Hespanha (2004). Meanwhile, some literature has taken channel conditions into account. Quevedo, Ahlén, and Østergaard (2010) studied state estimation over fading channels. They proposed a predictive control algorithm, where power and cookbooks are determined in an online fashion based on the undergoing estimation error covariance and the channel gain predictions. More related works can been seen in Leong and Dey (2012), Nourian, Leong, Dey, and Quevedo (2014) and Quevedo, Ahlén, Leong, and Dey (2012).

An important issue which has not been taken seriously in most works is that the transmission power assignment, as a tool to control the accessibility of information to the receiver, should be determined not only by the underlying channel condition and the desired estimation performance, but also by the transmitted information itself. In Leong and Dey (2012) and Quevedo et al. (2010), the authors failed to associate transmission power with data to be sent. The plant states are used to determine the transmission power in Gatsis, Ribeiro, and Pappas (2013). In this case, lost packets signal the receiver of the state information. To avoid computation difficulty, the signaling information is discarded.

In this paper, we focus on how to adapt the transmission power to the measurements of plant state and how to exploit information contained in the lost packets. We propose a data-driven power controller, which utilizes different transmission power levels to send the local estimate according to a quadratic function of a key parameter called "incremental innovation" which is evaluated by the sensor at each time slot. By doing this, even when data dropouts occur, the remote estimator can utilize the additional

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signaling information to refine the posterior probability density of the estimation error by a Bayesian inference technique (see Box & Tiao, 2011), therefore deriving the MMSE estimate. It compensates the deteriorated estimation performance caused by packet losses. To facilitate analysis, we assume that a baseline power controller has already been established based on different factors with regard to different settings, such as the requirement of estimation performance as in Shi and Xie (2012) or the channel conditions as in Leong and Dey (2012) and Quevedo et al. (2012, 2010). We are devoted to developing a power controller that embellishes this baseline controller by adapting the transmission power to the measurements such that the averaged power with respect to all possible values taken by the measurements does not exceed that of the baseline power controller. The proposed power controller, driven by online measurements, can run on top of non-data-driven power controllers, which results in hierarchical power control mechanisms. Then extension to a time-varying power baseline is established in Section 4.4. Note that a related controller was first proposed in Li, Quevedo, Lau, and Shi (2013), but as a special case of the controller in this work. The main contributions of the present work are summarized as follows.

(1) We propose a data-driven power control strategy for state estimation with packet losses, which adapts the transmission power to the measured plant states.
(2) We prove that the proposed power controller preserves Gaussianity of the local innovation. It simplifies derivation of the MMSE estimate and leads to a closed-form expression of the expected state estimation error covariance.
(3) We present a tuning method for parameter design. Despite its sub-optimality, the controller is shown to perform not worse than an alternative non-data-driven one.

The remainder of this paper is organized as follows. In Sections 2 and 3, we give mathematical models of the considered system and introduce the data-driven transmission power controller. In Section 4, we present the MMSE estimate at the remote estimator and a sub-optimal power controller that minimizes an upper bound of the remote estimation error. In Section 5, comparisons with alternative non-data-driven controllers demonstrate performance improvement using our approach. Section 6 presents concluding remarks.

Notation: $\mathbb{N}$ (and $\mathbb{N}_+$) is the set of nonnegative (and positive) integers. $\mathbb{S}_+^n$ is the cone of n by n positive semi-definite matrices. For a matrix X, $\lambda_i(X)$ is the ith smallest nonzero eigenvalue. We abuse notations $\det(X)$ and X^{-1}, which are used, in case of a singular matrix X, to denote the pseudo-determinant and the Moore–Penrose pseudoinverse. δ_{ij} is the Dirac delta function, i.e., δ_{ij} equals 1 when $i=j$ and 0 otherwise. The notation pdf($\mathbf{x}$, x) represents the probability density function (pdf) of a random variable $\mathbf{x}$ taking value at x.

2. State estimation using a smart sensor

Consider a linear time-invariant (LTI) system:

$$x_{k+1} = Ax_k + w_k, \tag{1}$$

$$y_k = Cx_k + v_k, \tag{2}$$

where $k \in \mathbb{N}$, $x_k \in \mathbb{R}^n$ is the system state vector at time k, $y_k \in \mathbb{R}^m$ is the measurement obtained by the sensor, the state noise $w_k \in \mathbb{R}^n$ and observation noise $v_k \in \mathbb{R}^m$ are zero-mean i.i.d. Gaussian noises with $\mathbb{E}[w_k w_j'] = \delta_{kj} Q$ ($Q \succeq 0$), $\mathbb{E}[v_k (v_j)'] = \delta_{kj} R$ ($R \succ 0$), $\mathbb{E}[w_k (v_j)'] = 0\ \forall j, k \in \mathbb{N}$. The initial state x_0 is a zero-mean Gaussian random vector with covariance $\Pi_0 \succeq 0$ and is uncorrelated with w_k and v_k. (A, C) is assumed to be detectable and $(A, Q^{1/2})$ is assumed to be stabilizable. Furthermore, we assume A is Hurwitz. [1]

2.1. Sensor local estimate

Hovareshti, Gupta, and Baras (2007) illustrated that utilization of the computation capabilities of wireless sensors may improve the system performance significantly. Equipped with such "smart sensors", the sensor locally runs a Kalman filter to produce the MMSE estimate $\hat{x}_k^s$ of the state x_k based on all the measurements collected up to time k, i.e., $y_{1:k} \triangleq \{y_1, \ldots, y_k\}$, and then transmits its local estimate to the remote estimator. Denote the sensor's local MMSE state estimate, the corresponding estimation error and error covariance as $\hat{x}_k^s$, e_k^s and P_k^s, respectively, i.e., $\hat{x}_k^s \triangleq \mathbb{E}[x_k | y_{1:k}]$, $e_k^s \triangleq x_k - \hat{x}_k^s$ and $P_k^s \triangleq \mathbb{E}[(x_k - \hat{x}_k^s)(x_k - \hat{x}_k^s)' | y_{1:k}]$. Standard Kalman filtering analysis suggests that these quantities can be calculated recursively (cf., Anderson & Moore, 1979), where the recursion starts from $\hat{x}_0^s = 0$ and $P_0^s = \Pi_0 \succeq 0$. Since P_k^s converges to a steady-state value exponentially fast (cf., Anderson & Moore, 1979), we assume that the sensor's local Kalman filter has entered the steady state, that is, $P_k^s = \overline{P} \succeq 0\ \forall k \in \mathbb{N}$, This assumption simplifies our subsequent analysis and results, such as Theorem 4.8 and Proposition 4.17.

2.2. Wireless communication model

The data are sent to the remote estimator over an Additive White Gaussian Noise (AWGN) channel using the Quadrature Amplitude Modulation (QAM) whereby $\hat{x}_k^s$ is quantized into K bits and mapped to one of 2^K available QAM symbols.[2] For simplicity, the following assumptions are made:

A.1: The channel noise is independent of w_k and v_k.
A.2: K is large enough so that quantization effect is negligible when analyzing the performance of the remote estimator.
A.3: The remote estimator can detect symbol errors.[3] Only the data arriving error-free are regarded as being successfully received; otherwise they are regarded as dropout.

These assumptions are commonly used in communication and control theories (cf., Fu & de Souza, 2009, Gatsis et al., 2013, Leong & Dey, 2012, Quevedo et al., 2010 and Sinopoli et al., 2004). For example, Fu and de Souza (2009) demonstrated that the estimation quality improvement (in terms of reduction of the remote estimation error) achieved by increasing the number K of the quantization bits is marginal when K is sufficiently large (in their example K only needs to be greater or equal to 4. Based on A.3, the communication channel can be characterized by a random process $\{\gamma_k\}_{k \in \mathbb{N}_+}$, where

$$\gamma_k = \begin{cases} 1, & \text{if } \hat{x}_k^s \text{ arrives error-free at time } k, \\ 0, & \text{otherwise,} \end{cases}$$

initialized with $\gamma_0 = 1$. Denote $\gamma_{1:k} \triangleq \{\gamma_1, \ldots, \gamma_k\}$. Let $\omega_k \in [0, +\infty)$ be the transmission power for the QAM symbol at time k. We adopt the wireless communication channel model used in Li et al. (2013), and have $\Pr(\gamma_k = 0 | \omega_k) = q^{\omega_k}$, where q is given by $q \triangleq \exp(-\alpha/(N_0 W)) \in (0, 1)$, N_0 is the AWGN noise power spectral density, W is the channel bandwidth, and $\alpha \in (0, 1]$ is a constant that depends on the specific modulation being used. To send local estimates to the remote estimator, the sensor chooses from a continuum of available power levels $\omega_k \geqslant 0$, see Fig. 1. Note that different power levels lead to different dropout rates, thereby affecting estimation performance.

[1] Since we focus on remote state estimation in this paper, for any practically working systems (to be monitored alone), A has to be Hurwitz. Otherwise, the system state will go unbounded and there is no real sensing device which can track an unbounded state trajectory. Adding a control input to regulate the system state for an unstable A and studying its associated stability issue will be beyond the scope of this paper and will be left as our future work.

[2] QAM is a common modulation scheme widely used in IEEE 802.11g/n as well as 3G and LTE systems, due to its high bandwidth efficiency.

[3] In practice, symbol errors can be detected via a cyclic redundancy check (CRC) code.