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Brief paper

Transmit power control and remote state estimation with sensor networks: A Bayesian inference approach ☆

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ABSTRACT

In this work, a multi-sensor transmit power control design problem for remote state estimation over a packet-dropping network is investigated. In this problem, a remote estimator collects measurement innovations from each individual sensor node for data fusion, where the dropouts of data packets may occur over the communication network. Subject to an energy constraint, we propose a transmit power controller for each sensor based on a quadratic form of the measurements' incremental innovation. Under this specific form of transmit power controller which is proved to preserve the Gaussianity of the *a posteriori* state estimation, we derive the minimum mean squared error (MMSE) estimate for the remote state estimator with a closed-form recursion of the expected estimation error covariance. Performance analysis is also provided. For scalar systems, an upper bound of the expected estimation error variance is optimized subject to a limited energy budget over the parameters of the proposed power controller. Numerical comparisons with other controllers are made to illustrate the performance of our approach.
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1. Introduction

Wireless sensor networks (WSNs) consist of a collection of spatially distributed sensing nodes—the amount may vary from a few to hundreds or even thousands. The nodes, which are interconnected, collect environmental information from the physical world and pass their data to a data center through a communication network, realizing an integration of the information space and the physical world. Remote estimation of environmental physical conditions, which is often implemented recursively using a Kalman filter, is a core problem of WSNs. With the growing spectrum of applications, WSNs can be found in various areas such as unmanned aerial vehicles, smart grids, remote surgery, automated highway systems and environment monitoring (Pantazis & Vergados, 2007; Yick, Mukherjee, & Ghosal, 2008). Naturally, the industrial installations of WSNs are increasing tremendously and the state estimation with WSNs has become a hot research area since the recent few years.

Though the wide use of wireless sensors offers considerable advantages, such as low cost, easy installation and self-power (Gharavi & Kumar, 2003), the potential shortcomings of wireless communication, e.g., channel fading and interference, may lead to packet dropouts and estimation performance degradation (Proakis & Salehi, 2007). A comprehensive framework, which takes communication constraints into account in solving the estimation problem, will, in general, provide better tradeoffs between performance and energy usage trade-offs; substantial efforts are made in Marques, Wang, and Giannakis (2008), Pantazis and Vergados (2007), Quevedo, Ahlén, and Østergaard (2010), Shi, Cheng, and Chen (2011), Wu, Jia, Johansson, and Shi (2013), Xiao, Cui, Luo, and Goldsmith (2006) and Zhang, Poor, and Chiang (2008).

Energy saving is a crucial issue for most wireless sensors as they are equipped with on-board batteries, which are difficult to replace and typically are expected to work for years without replacement due to environment or sensor limitations (Yick et al., 2008). Wireless communication cost at many operational modes, such as transmit and receive, is the dominating factor affecting the battery power consumption. Therefore transmit power control becomes crucial for WSNs. Transmit power control is desired to mitigate the inevitable enlarged estimation error due to limited energy budget. Based on whether utilizing the real-time system information for decision, there are two major categories of power control, namely, the offline control and the online (event-based) control. The former one could be found in the work (Shi et al., 2011; Trimpe & D'Andrea, 2014), which can be regarded as a simplified

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version of the sensor power control problem, namely, the sensor schedule problem where a two-level transmit power (transmission or not) model is adopted. A more general offline transmit power model was given in Li, Quevedo, Lau, and Shi (2013b). On the other hand, the works in Weerakkody, Mo, Sinopoli, Han, and Shi (2016), Wu et al. (2013) and Wu, Li, Quevedo, Lau, and Shi (2015) suggested that using what amount of energy to transmit data packets, which determines the information accessibility to the receiver, should be designed not only based on the channel condition, but also based on the real-time system information contained in the transmitted data. Several pieces of work assumed a pre-defined and constant channel properties and investigate the communication control problem. In Molin and Hirche (2012), any communication incurred a fixed constant energy consumption. A stochastic event-based sensor scheduling problem, where the decision variable is to send or not, was studied in Han et al. (2015); with Weerakkody et al. (2016) extending this method to the multi-sensor scheduling scenario. To better address the impact of channel condition on communication, several papers considered transmit power control based on a more practical communication channel model involving the relationship between the signal to noise ratio (SNR) and the symbol error rate (SER). The work in Li, Quevedo, Lau, and Shi (2013a) and Wu et al. (2015) adopt a general communication channel model where the sensor's local state estimate was communicated to the remote estimator over an additive white Gaussian noise (AWGN) channel using quadrature amplitude modulation (QAM). Different power levels lead to different dropout rates, and thereby affect estimation performance.

In this paper, we focus on a transmit power control for remote estimation using multiple sensors. The transmit power controller is designed as a function of the incremental innovation evaluated from measurement at each time. Under such a power control policy, for the case when a packet dropout occurs, the remote estimator can still obtain side information from the communication result provided that it is able to know the present channel state information (CSI). As a result, the estimator could update the posterior probability density of the state to be estimated based on a Bayesian inference method (Box & Tiao, 2011), with the inferred side information helping reduce the estimation error covariance. By approximating the symbol error rate of the adopted M-ary quadrature amplitude modulation (M-QAM) scheme into an exponential function, we choose the transmit power controller as a quadratic form of the incremental innovation, which enables us to compute the MMSE state estimate and corresponding error covariance recursively. The expected energy consumption and the average data packet arrival rate are analyzed. Then for scalar systems, we optimize an upper bound of the estimation error variance subject to a limited energy budget over parameters of the power controller. This paper extends the existing results for the single sensor case such as the one in Wu et al. (2015) to the multi-sensor case. Compared with the single sensor case, new challenges brought by multiple sensors data fusion and the state estimation error covariance are derived. In particular, the main contributions of the paper are summarized as follows:

(1) Under the specific power controller proposed in the present work, we prove that the *a posterior* probability density of the state remains Gaussian. Based on a Bayesian inference method, we derive a closed-form MMSE state estimator.
(2) Due to the randomness of packet arrivals, the state estimation error covariance matrices may not converge to a steady-state value. We investigate the statistical property of the covariance matrices and provide an upper bound of the state estimation error covariance matrices at each time step.
(3) We optimize parameters of the power controller for scalar systems and obtain a closed-form solution.

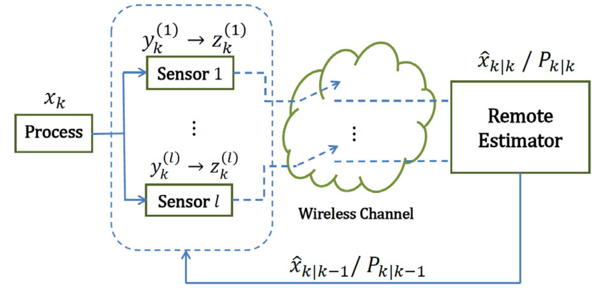

Fig. 1. System architecture.

The remainder of the paper is organized as follows. Section 2 presents the system model. Section 3 designs the transmit power controller and studies the remote state estimator. System performance under the proposed controller is analyzed in Section 4. Numerical simulations are given in Section 5. Section 6 draws some concluding remarks.

Notation: $\mathbb{N}$ and $\mathbb{R}_+$ are the sets of nonnegative integers and positive real numbers, respectively. The notation $p(\mathbf{x}; x)$ represents the probability density function (pdf) of a random variable $\mathbf{x}$ taking value at x. If it is clear in the context, $\mathbf{x}$ is omitted. Let $X \in \mathbb{R}^{m\times n}$ and $x \in \mathbb{R}^n$. For index sets $\alpha \subset \{1, \dots, m\}$ and $\beta \subset \{1, \dots, n\}$, we denote the vector that consists of the entries indexed by β as $x[\beta]$ and the matrix that lies in the rows of X indexed by α and the columns indexed by β as $X[\alpha, \beta]$. For simplicity, let $X[\beta] \triangleq X[\beta, \beta]$. $\mathbb{S}_+^n$ (or $\mathbb{S}_{++}^n$) is the set of n by n positive semi-definite (or positive definite) matrices. When $X \in \mathbb{S}_+^n$ (or $\mathbb{S}_{++}^n$), we write $X \geqslant 0$ (or $X > 0$). $X \geqslant Y$ if $X - Y \in \mathbb{S}_+^n$. $\mathrm{Tr}(\cdot)$ and $|\cdot|$ are the trace and the determinant, respectively, of a matrix. The superscript $^\top$ stands for transposition. To simplify notations, we define the Lyapunov operator $h : \mathbb{S}_+^n \to \mathbb{S}_+^n$ as: $h(X) \triangleq AXA^\top + W$.

2. System model

In this section, we introduce the preliminaries of the system model.

2.1. Sensor network

We consider a discrete-time linear time-invariant (LTI) system, which is observed by a network of sensors indexed by the set $\mathcal{V} = \{1, \dots, l\}$:

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

$$y_k^{(i)} = C^{(i)}x_k + v_k^{(i)}, \tag{1b}$$

where $k \in \mathbb{N}$, $i \in \mathcal{V}$, $x_k \in \mathbb{R}^n$ is the system state vector at time k, $y_k^{(i)} \in \mathbb{R}^{m^{(i)}}$ is the observation obtained by the ith sensor. The system noise $w_k \in \mathbb{R}^n$, the measurement noise $v_k^{(i)} \in \mathbb{R}^{m^{(i)}}$ of sensor i and the initial system state x_0 are pairwise independent zero-mean Gaussian random variables with covariances W, $R^{(i)} > 0$ and $\Sigma_0 \geq 0$ respectively. Denote $C \triangleq [C^{(1)^\top}, \dots, C^{(l)^\top}]^\top$ and $R \triangleq blkdiag(R^{(1)}, \dots, R^{(l)})$, where the operator $blkdiag(\cdot)$ denotes the block diagonal matrix consisting of the corresponding matrices as diagonal blocks. When no ambiguity arises, we will use $\mathrm{diag}(\cdot)$ instead of $blkdiag(\cdot)$ to simplify the notation. Assume that (A, C) is detectable.

We assume that the remote estimator (usually more powerful in resource than sensors) broadcasts its *a priori* estimate $\hat{x}_{k|k-1}$, which will be formally defined later in (10) with the corresponding

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