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Multi-rate distributed fusion estimation for sensor networks with packet losses☆

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ABSTRACT

This paper presents a distributed fusion estimation method for estimating states of a dynamical process observed by wireless sensor networks (WSNs) with random packet losses. It is assumed that the dynamical process is not changing too rapidly, and a multi-rate scheme by which the sensors estimate states at a faster time scale and exchange information with neighbors at a slower time scale is proposed to reduce communication costs. The estimation is performed by taking into account the random packet losses in two stages. At the first stage, every sensor in the WSN collects measurements from its neighbors to generate a local estimate, then local estimates in the neighbors are further collected at the second stage to form a fused estimate to improve estimation performance and reduce disagreements among local estimates at different sensors. Local optimal linear estimators are designed by using the orthogonal projection principle, and the fusion estimators are designed by using a fusion rule weighted by matrices in the linear minimum variance sense. Simulations of a target tracking system are given to show that the time scale of information exchange among sensors can be slower while still maintaining satisfactory estimation performance by using the developed estimation method.

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1. Introduction

A wireless sensor network (WSN) consists of spatially distributed autonomous sensors to cooperatively monitor physical or environmental conditions. The purpose of a WSN is to provide users access to the information of interest from data gathered by spatially distributed sensors. In most applications, users are interested in a processed data that carries useful information of a physical plant rather than a measured data contaminated by noises. Therefore, it is not surprising that signal estimation has been one of the most fundamental collaborative information processing problems in WSNs (Dogandžić & Zhang, 2006; Ribeiro, Schizas, Roumeliotis, & Giannakis, 2010).

However, it is known that the WSNs are usually severely constrained in energy, and energy-efficient methods are thus important for WSN based estimation to reduce energy consumption and to prolong network life. Consider the situation where a WSN is deployed to observe and estimate states of a dynamically changing process, but the process is not changing too rapidly. Then it is wasteful from an energy perspective for sensors to transmit every measurement to an estimator to generate estimates, and this waste is amplified by packet losses which are usually unavoidable in WSNs (Kar, Sinopoli, & Moura, 2012; Shen, Wang, & Hung, 2010; Sinopoli et al., 2004; Sun, Xie, Xiao, & Soh, 2008; Wang, Ho, & Liu, 2003; Wang, Yang, Ho, & Liu, 2005; Xiao, Xie, & Fu, 2009; Zhang, Yu, & Song, 2009). Though there have been some energy-efficient estimation methods in the literature, such as the quantization method (Li & AlRegib, 2009; Msechu, Roumeliotis, Ribeiro, & Giannakis, 2008; Xiao, Cui, Luo, & Goldsmith, 2006) and the data-compression method (Chen, Zhang, & Li, 2004; Schizas, Giannakis, & Luo, 2007; Zhu, Schizas, & Giannakis, 2009), they are not helpful in dealing with the above raised problem, because the main idea in quantization and compression is to reduce the size of a data packet and thus to reduce energy consumption in transmitting and receiving packets. Actually, an useful and straightforward approach to saving energy in the above considered estimation problem is to slow down the information transmission rate in the sensors, for example, the sensors may measure and transmit measurements with a period that is several times of the sampling period. This method might thus be intuitively called as a *transmission rate method*. Few results on this method have been reported for WSN based estimation except for Liang, Chen, and Pan (2009), and the main difficulty

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of using this method is that it may result in multi-rate estimation systems.

On the other hand, signal estimations in WSN could be done under the end-to-end information flow paradigm by communicating all the relevant data to a central collector node, e.g., a sink node. This however is a highly inefficient solution in WSN, because it may cause long packet delay, consume large amount of energies and it has the potential for a critical failure point at the central collector node. An alternative solution is for the estimation to be performed *in-network* (Dimakis, Kar, Moura, Rabbat, & Scaglione, 2010; Giridhar & Kumar, 2006), i.e., every sensor in the WSN with both sensing and computation capabilities performs not only as a sensor but also as an estimator, and it collects measurements only from its neighbors to generate estimates. It is obvious that local estimates obtained at each sensor by such a distributed *in-network* method are not optimal in the sense that not all the measurements in the WSN are used. Moreover, there exist disagreements among local estimates obtained at different sensors. In other words, local estimates at any two sensors may be different from each other. As pointed out in Olfati-Saber (2007), such form of group disagreement regarding the signal estimates is highly undesirable for a peer-to-peer network of estimators. This gives rise to two issues that should be considered in designing a distributed estimation algorithm: (1) how could each sensor improve its local performance by taking full use of limited information from its neighbors? (2) how to reduce disagreements of local estimates among different sensors? A consensus strategy (Carli, Chiuse, Schenato, & Zampieri, 2008; Kar & Moura, 2011; Olfati-Saber, 2007, 2005; Schizas, Ribeiro, & Giannakis, 2007; Xiao, boyd, & Kim, 2006) and a diffusion strategy (Cattivelli & Sayed, 2010) have been presented in the literature to deal with the aforementioned two issues, where the consensus strategy mainly focuses on issue (1) while the diffusion strategy mainly focuses on issue (2). The main idea of the consensus strategy is that all sensors should obtain the same estimate in steady-state by using some consensus algorithms. In the diffusion strategy, both measurements and local estimates from neighboring sensors are used to generate estimates at each sensor. However, the energy-efficiency issue is not considered in both the consensus and diffusion strategies which usually require frequent information exchange among sensors to reach a common state and improve each local estimate. These motivate us to use the *transmission rate method* to design an energy-efficient fusion estimation method for the WSN based distributed estimation system with slowly changing dynamics and packet losses, and provide a solution to the problems raised in issues (1) and (2).

In this paper, the WSN is considered to be a peer-to-peer network without a fusion center, and every sensor in the network collects information only from its neighbors to generate estimates. A multi-rate scheme by which the sensors estimate states at a faster time scale and exchange information with neighbors at a slower time scale is proposed to reduce communication costs. Packets exchanged among the sensors may be lost during the transmission and several binary-valued white Bernoulli sequences are used to describe the random packet losses. Then, by applying a lifting technique as used in Liang et al. (2009); Liang, Chen, and Pan (2010), the multi-rate estimation system is finally modeled as a single-rate discrete-time system with multiple stochastic parameters. Based on the obtained system model, the distributed fusion estimation is carried out in two stages. At the first stage, every sensor in the WSN collects measurements from neighboring sensors to generate a local estimate, then local estimates from neighboring sensors are further collected to form a fused estimate at the second stage. By fusion of both measurements and local estimates, more information from different sensors are used to generate estimates in the two-stage method as compared with the one-stage one where only measurements are collected to generate estimates. Therefore, the proposed two-stage estimation method helps steer each local estimate closer to the global optimal one and thus helps reduce disagreements of local estimates among different sensors. Then, by using the orthogonal projection principle and the innovation analysis approach, an estimation algorithm with a set of recursive Lyapunov and Riccati equations is presented to design the distributed estimators. The obtained estimation performances critically depend on the information transmission rate and the packet loss probabilities, and it is demonstrated by a simulation example of a maneuvering target tracking system that the time scale of information exchange among sensors can be slower while still maintaining satisfactory estimation performance by using the proposed estimation method.

The rest of the paper is organized as follows. In Section 2, the multi-rate estimation system model is described and the distributed estimation problem is formulated. Then, design procedures for the fusion estimators are presented in Section 3. The effectiveness of the proposed estimators is demonstrated by an illustrative example in Section 4. Finally, the conclusion is provided in Section 5.

Notation. $\text{diag}\{\cdot\}_m$ stands for a block-diagonal matrix with m elements in the diagonal, $\text{col}\{x_i\}_{i\in\phi}$ represents a column vector composed of elements x_i, $i \in \phi$, $[a_{ij}]$, $i, j \in N$ stands for a matrix composed of elements a_{ij}, $i, j \in N$, $\text{Prob}\{A\}$ means occurrence probability of the event A, $\text{proj}\{\cdot\}$ is the projection operator, $L(x_1, x_2, \ldots)$ denotes the linear span of the vectors $x_1, x_2, \ldots, x \perp y$ denotes orthogonal vectors x and y, $\text{Tr}(A)$ denotes the trace of matrix A.

2. Models and problem statement

Consider a linear discrete-time stochastic system described by the following state-space model

$$x(k_{i+1}) = A_p x(k_i) + B_p \omega_p(k_i), \quad i = 0, 1, 2, \ldots \tag{1}$$

where $x(k_i) \in \Re^n$ is the system state, $\omega_p(k_i) \in \Re^p$ is a zero mean white noise, $h_p = k_{i+1} - k_i, \forall i = 0, 1, 2, \ldots$ is the sampling period of system (1). A WSN consisting of N spatially distributed sensors is deployed to collect observations of system (1) according to the following observation models:

$$y_l(k_i) = C_{pl} x(k_i) + D_{pl} \upsilon_{pl}(k_i), \quad l = 1, \ldots, N, \tag{2}$$

where $y_l(k_i) \in \Re^{m_l}$ is the observation collected by sensor l at time instant k_i, $\upsilon_{pl}(k_i) \in \Re^{q_l}$ are white measurement noises with zero means, A_p, B_p, C_{pl}, and D_{pl} are constant matrices with appropriate dimensions. $\omega_p(k_i)$ is uncorrelated with $\upsilon_{pl}(k_i)$, while $\upsilon_{pl}(k_i)$ are mutually correlated, and $\mathbf{E}\{\omega_p(k_i)\omega_p^T(k_j)\} = Q_{\omega_p}\delta_{ij}$, $\mathbf{E}\{\upsilon_{pl}(k_i)\upsilon_{ps}^T(k_j)\} = Q_{l,s}^{\upsilon_p}\delta_{ij}$, $l, s \in Z_0$, where $\delta_{ii} = 1$ and $\delta_{ij} = 0\,(i \neq j)$.

The WSN is considered to be a peer-to-peer network, there is no fusion center in the network, and every sensor in the network acts also as an estimator. The observations are transmitted among the sensors in an ad-hoc manner via unreliable wireless communication channels and may be subject to random packet losses. We say that two sensors are connected if they can communicate directly with each other, i.e., they can communicate with each other within one hop. Notice that a sensor is always connected to itself. The set of sensors connected to a certain sensor r is called the neighborhood of sensor r and is denoted by $\mathcal{N}_r$, $r \in Z_0 \triangleq \{1, \ldots, N\}$ (notice that $r \in \mathcal{N}_r$), and the number of neighbors of sensor r is given by the number of elements of $\mathcal{N}_r$, written as n_r. Denote by $L_{i,j}$, $i, j \in \mathcal{N}_r$ the link between sensor i and sensor j in a neighborhood. Then, the random packet loss in the link $L_{i,j}$ is described by a white binary distributed random process

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