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Diffusion Kalman filtering with multi-channel decoupled event-triggered strategy and its application to the optic-electric sensor network

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ABSTRACT

Recently the distributed estimation problem with communication constraints has been widely studied for sensor network application. Our work focus on the diffusion Kalman filter with communication constraints. To satisfy finite communication resources constraints, this paper presents a multi-channel decoupled event-triggered strategy which improves the utilization of the network communication resources. With this strategy, only some entries of sensors' measurements are transmitted if their triggering criteria are satisfied. We apply this strategy to the step 1 of the diffusion Kalman filter and analyze its performance. The analysis shows that the multi-channel decoupled event-triggered diffusion Kalman filter is unbiased in mean sense and is convergent in mean-square sense. The theoretical steady-state mean-square deviation (MSD) and communication cost are also given in this article. Simulation results demonstrate a good match between the theory analysis and experiment. Finally this algorithm is applied to the optic-electric sensor network, and the results verify the effectiveness of the proposed strategy in terms of the communication resources utilization.

1. Introduction

As one of the important issues in information fusion, the state estimation problem for linear or nonlinear systems has been a focus of research because of its clear engineering insights in many practical applications [1–6]. Due to the scalability and robustness of the distributed estimation algorithm, a lot of efforts have been made to improve its performance [7–10]. Diffusion strategy [9,10] is an effective approach to perform distributed estimation over sensor networks.

In the step 1 of the diffusion Kalman filter algorithm [11], all the sensors in the network transmit their information about the system state to their neighbors, then each sensor fuses the information received together with its own to create an intermediate estimate. In the step 2, i.e., the diffusion step, each sensor combines its intermediate estimate and its neighbors' to obtain the final estimate. This in-network cooperation helps the information propagate across the network so that all nodes benefit from data of the entire network. As a consequence, all nodes in the network asymptotically perform as well as the centralized case.

However, the main disadvantage of the diffusion Kalman filter is that it needs a lot of internode communications. As all the sensors in the network communicate with all their neighbors, the amount of required internode communication is huge. In practical, the energy of sensors for data collection and transmission is limited [12]. It's an expensive operation to replace or recharge batteries of sensors in many applications. A large communication cost imposes a restriction on the application of the diffusion Kalman filter algorithm. Therefore it is of great practical significance to reduce the amount of the internode communication while maintaining the advantage of the in-network cooperation as much as possible.

In order to reduce the communication cost of the sensor network, several approaches have been proposed.

Firstly, this problem can be studied from the digital communication point of view that sensors limit the number of binary bits that they send [13–15]. Secondly, the decreasements of sensors' sending counts help the network reduce its communication amount. In [16,17], the network communication cost is reduced by slowing down the transmission rate of each sensor. In [18–21], each communication link is intermittently activated, hence the amount of total internode communication in the network is reduced. A partial diffusion strategy has been proposed in [22] to reduce the internode communication cost while retaining the

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benefits of the in-network cooperation. Thirdly, the concept of the set-membership filter has been utilized in [23–25] to alleviate the network communication cost.

At last, the event-triggered strategy is an efficient approach to deal with this problem. In [26–28], the measurements are transmitted when the triggering criteria are satisfied and the state estimators have been derived to cope with the event-based measurements. Unlike the deterministic event-triggered strategy [26–28], through utilizing the stochastic event-triggered sensor schedule, a minimum mean squared error estimator has been given in a closed-form while maintaining the Gaussian property of the innovation process [29–31]. The event-triggered state estimation problem for complex networks with mixed time delays was studied in [32], and the estimator gain matrices are obtained by solving a convex problem. The authors studied the event-triggered optimal state estimation problem for linear time-varying systems with a unknown input in [33], and the minimum mean squared error estimator is obtained by treating the unknown input as a process with a non-informative prior. In [34], the authors studied the problem of estimating the state of a discrete-time linear stochastic dynamical system with a data-driven strategy, and the cases of measurement transmission and local estimate transmission were both studied. In [35], a general event-triggered framework has been proposed to deal with the variance-constrained H_∞ control problem for a class of discrete time-varying systems with randomly occurring saturations, stochastic nonlinearities and state-multiplicative noises. A novel definition of consensus in probability has been proposed in [36] to deal with the event-triggered consensus control problem for a class of discrete-time stochastic multi-agent systems. In [37], the consensus control problem has been investigated for a class of discrete time-varying stochastic multi-agent systems with the event-triggered mechanism. The authors have studied the distributed event-based filtering problem in [38–43] and have made several important achievements.

The above results take all the entries of the measurement or the state vector into the triggering criteria [26–34,38–43]. However in practical, the variety degrees of entries of the state vector are different, so the variety degrees of entries of the measurement are different as well. That is to say, during a period of time, some entries of the measurement may vary rapidly, while others may vary gently or even stay the same. Thus if we take all the entries of a measurement into one triggering criterion, the entries which vary gently will be transmitted with the ones that vary rapidly. It's a waste of the communication resources. Therefore if we design a suitable triggering criterion for each entry of the measurement, the communication resources will be utilized further efficiently.

Through utilizing the multi-channel decoupled event-triggered strategy in the step 1 of the diffusion Kalman filter, each sensor node transmits a subset of entries of its measurement to its neighboring nodes only when the corresponding triggering criteria are satisfied, the internode communication cost of the diffusion Kalman filter algorithm will be reduced.

Remark 1.1. The strategy proposed in this article is similar as the partial diffusion policy proposed in [22]. The differences between our work and [22] are summarised as follows. Firstly, the entries which are sent in [22] are selected randomly or sequentially. While in our work, the entries' transmissions are based on their triggering criteria. Secondly, in [22] the intermediate estimates are transmitted by the partial diffusion strategy, while in our work, the measurements' transmissions are based on their triggering criteria. Finally, the distributed least mean square estimation algorithm is performed in [22] to estimate a time-invariant vector, while in this paper a multi-channel decoupled event-triggered diffusion Kalman filter is proposed to estimate the state of a stochastic process.

The main contributions of our work are summarized as follows.

(1) The multi-channel decoupled event-triggered strategy is proposed in this paper. With the proposed strategy, the transmissions of measurements' entries are based on their event-triggering criteria. Comparing with the typical event-triggered strategies, the sensor network's communication resources will be utilized more efficiently, and this coincides with the results of the simulation.
(2) The proposed strategy is applied to the step 1 of the diffusion Kalman filter. With the proposed strategy, the communication cost of the network is reduced. We analyze the performance of the multi-channel decoupled event-triggered diffusion Kalman filter in mean sense and mean-square sense. We also derive the steady-state estimation error covariance matrix of this algorithm.
(3) The proposed algorithm is applied to the optic-electric sensor network. The results show that the proposed algorithm helps the optic-electric sensor network utilize its communication resources efficiently. In other words, with the proposed strategy, the optic-electric sensors transmit their information only when they are needed. It's of significance in practical.

The remainder of the paper is organized as follows. Section 2 formulates the estimation problem and proposes the multi-channel decoupled event-triggered strategy. Section 3 presents the multi-channel decoupled event-triggered diffusion Kalman filter algorithm. Section 4 shows the analysis results on the performance of the proposed algorithm. Section 5 presents some simulation results. Section 6 presents the application of the proposed algorithm in the optic-electric sensor network. Conclusion is given in the end.

In this article, $\mathrm{col}_i\{a_i\}$ denotes a vector with entries a_i, $\mathrm{diag}_i\{b_i\}$ denotes a diagonal matrix with diagonal entries b_i. $\otimes$ denotes the Kronecker product. Let $m, n \in \mathbb{N}^+$, $\mathbb{R}^{m\times n}$ denotes the set of m by n real-valued matrices. R^{T} denotes the transposition of matrix R. For $X, Y \in \mathbb{R}^{m\times m}$, $X > (\geq) Y$ means $X - Y$ is positive definite(positive semidefinite). $\mathbb{E}[\cdot]$ denotes the expectation operator. trace(R) denotes the trace of matrix R. $\xi_{M,\delta} = \{\zeta | \zeta^{\mathrm{T}} M \zeta \leq \delta\}$ denotes an ellipsoidal set centered at the origin associated with M and δ. I denotes the identity matrix with a suitable dimension.

2. Problem setup

Consider the following linear discrete-time system,

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

where $x_k \in \mathbb{R}^n$ is the system state at time k. The signal w_k denotes the process noise.

The system (1) is observed by a sensor network which is consisted of M sensor nodes. The network's topology is denoted by $\mathbb{G}$. Γ denotes the adjacency matrix of $\mathbb{G}$. Two nodes are connected if they can communicate directly with each other . The set of nodes that are connected to node i is called the neighborhood of node i and is denoted by $\bar{N}_i$, $N_i = \bar{N}_i \cup \{i\}$.

The sensor i collects a measurement about x_k as

$$y_k^i = C^i x_k + v_k^i \tag{2}$$

where $y_k^i \in \mathbb{R}^m$ denotes the measurement of sensor i at time k. The signal v_k^i is the measurement noise of sensor i at time k. w_k and v_k^i are uncorrelated zero-mean Gaussian noises and satisfy

$$E\begin{bmatrix} w_k \\ v_k^i \end{bmatrix}\begin{bmatrix} w_j \\ v_j^i \end{bmatrix}^{\mathrm{T}} = \begin{bmatrix} Q_k & 0 \\ 0 & R_k^i \end{bmatrix}\delta_{kj},$$

where δ_{kj} is the Kronecker delta function.

In general, the variety degrees of entries of x_k are different, so the degrees of change of the corresponding entries of y_k^i are different as well. To make full use of the communication resources,