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Distributed information-weighted Kalman consensus filter for sensor networks☆

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ABSTRACT

Consensus-based algorithms for distributed Kalman filtering of the state of a dynamical target agent have attracted considerable research and attention during the past decade. In these filters, it is required for all agents to reach consensus about their estimates of the state of a target node. Distributed filtering techniques for sensor networks require less computation per sensor node and result in more robust estimation since they only use information from an agent's neighbors in a network. However, poor local sensor node estimates caused by limited observability, network topologies that restrict allowable communications, and communication noises between sensors are challenging issues not yet fully resolved in the framework of distributed Kalman consensus filters. This paper confronts these issues by introducing a novel distributed information-weighted Kalman consensus filter (IKCF) algorithm for sensor networks in a continuous-time setting. It is formally proven using Lyapunov techniques that, using the new distributed IKCF, the estimates of all sensors reach converge to consensus values that give locally optimal estimates of the state of the target. A new measurement model is selected that only depends on local information available at each node based on the prescribed communication topology, wherein all the estimates of neighbor sensors are weighted by their inverse-covariance matrices. Locally optimal solutions are then derived for the proposed distributed IKCF considering channel noises in the consensus terms. Moreover, if the target has a nonzero control input, a method is giving of incorporating estimates of the target's unknown input. Simulation case studies show that the proposed distributed IKCF outperforms other methods in the literature.

1. Introduction

This paper provides a novel algorithm for distributed Kalman filtering for multiple agents networked by a communication graph topology. In distributed filtering, each agent can only use information from its neighbors in a prescribed communication network. In addition, each agent must reach a consensus estimate that agrees with the estimates of all other nodes in the network. Consensus and synchronization in cooperative multi-agent systems has attracted a great deal of attention since the papers by Jadbabaie, Lin, and Morse (2003) and Olfati-Saber and Murray (2004). In this literature, protocols are sought to ensure synchronization of the states of all the agents to a common value. These protocols must respect the allowed communication links in that they are distributed in the sense that the computations of each agent depend only on the neighbors of that agent in the prescribed communication graph. The motivation for reaching consensus on the states of all agents arises in many fields, and consensus protocols have been applied to generate target velocity and position commands for networked vehicle formation control (Fax & Murray, 2004), to generate reference frequencies and voltages for synchronization in distributed energy generation microgrids

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(Bidram, Lewis, & Davoudi, 2014), for attitude synchronization in multiple satellites (Sahoo & Banavar, 2014), and to explain the synchronization of coupled oscillators (Strogatz & Stewart, 1993) and the reaching of agreement in human social networks (Wasserman & Faust, 1994). See the books Lewis, Zhang, Movric, and Das (2014), Qu (2009) for comprehensive treatments.

The computation of consensus values in the cooperative control literature has generally neither been optimal, nor taken into account channel transmission noises, nor quantified the accuracy of the consensus values reached. As such, the application of distributed Kalman filtering techniques to compute optimal consensus values of the states all agents in a networked team is a natural extension of the current literature.

Decentralized Kalman filtering techniques have attracted much attention and considerable research during the past few decades in sensor networks because they do not need a centralized processing station. The results include faster parallel processing and increased robustness to failures. Early works (Hashemipour, Roy, & Laub, 1988; Rao & Durrant-Whyte, 1991; Rao, Durrant-Whyte, & Sheen, 1993) were applied to data fusion by developing decentralized Kalman filtering algorithms. In Rao and Durrant-Whyte (1991), each node computed its own decentralized local estimate for an unknown target state vector, and a method was given for fusing or assimilating all the local estimates into a single estimate for the target state to accomplish globally optimal performance. Because the information flow is all-to-all with communication complexity of $O(N^2)$ (N is the number of sensors/nodes), this solution is not scalable for large-scale sensor networks, as stated in Olfati-Saber (2007). Communication complexity of Kalman consensus filtering depends on the information sent at each consensus step between sensors discussed in Kamal, Farrell, and Roy-Chowdhury (2012). It is evaluated quantitatively by communication bandwidth (BYTES/s) and computation burden (FLOPS/s) in Ferguson and How (2005). In these works, there was generally no requirement for all nodes to reach the same estimate of the target state.

Olfati-Saber (2007), states the difference between the decentralized Kalman filtering and distributed Kalman filtering. It is stated there "The decentralized Kalman filter in Rao et al. (1993) involves state estimation using a set of local Kalman filters that communicate with all other nodes. The information flow is all-to-all with communication complexity of $O(\mathrm{n}^2)$ which is not scalable for sensor networks.". Here, we focus on scalable or distributed Kalman Filtering algorithms in which each node only communicates messages with its neighbors on a network. Unlike the decentralized Kalman filtering in Rao and Durrant-Whyte (1991), the distributed Kalman filtering is more widely used for multi-sensor fusion and tracking problems recently where nodes need to reach consensus estimates at the cost of non-optimal estimates, due to their scalability for large networks and high fault tolerance. A comprehensive review of distributed state estimation approaches and comparisons with centralized and decentralized methods are detailed in Taj and Cavallaro (2011). Besides, the concerns of occlusions or limited observability of sensors in many applications domains, such as a distributed camera network detailed in Kamal, Farrell, and Roy-Chowdhury (2013), cannot be neglected, which motivates us to develop novel distributed filtering algorithms for data fusion against failure nodes in sensor networks.

The focus of this paper is the distributed Kalman consensus filtering problem, where the objective is to provide a good trade between accuracy and communication cost. The novel distributed Kalman filter could save communication costs in peer-to-peer information flow and improve the network robustness to possible failure of sensors simultaneously. In distributed consensus filtering, a graph topology is imposed that restricts inter-node communications, sensor nodes can directly use only information from local neighbors in the prescribed graph topology, locally optimal estimates are desired for the unknown target state at each node, and it is required that all local estimates eventually reach a consensus agreement about the values of their estimates of the target sensor state.

The work of Spanos, Olfati-Saber, and Murray (2005a) focuses on dynamic distributed sensor fusion to obtain consensus weighted least-squares fused estimates for multiple measurements. That paper does not include the dynamics of a target and no direct relation is drawn with the optimal Kalman filter. Sophisticated algorithms for diffusion implementation, distributed estimation and inference in sensor networks can be found in, e.g., Spanos, Olfati-Saber, and Murray (2005b,c) and Xiao, Boyd, and Lai (2006).

The work in Olfati-Saber (2005) and Olfati-Saber and Shamma (2005) presented distributed Kalman filtering algorithms, which consist of a network of micro-Kalman filters each embedded with a low-pass and a band-pass consensus filter. The Kalman consensus filter (KCF) proposed in Olfati-Saber (2007) has become a popular and efficient distributed consensus-based framework for dynamic state estimation, where each node sends/receives the measurements to/from only its local neighbors. A formal derivation, stability and performance analysis of KCF was given in Olfati-Saber (2009). The consensus terms in these papers are added in an ad hoc fashion outside the Kalman Filter framework. Moreover, in those works, inaccurate estimates of neighbors caused by limited observability are not discounted in the consensus algorithms. If neither a sensor (node) nor its immediate neighbors can receive messages from the target it is called a *Naive sensor node* in Kamal et al. (2013), where it was shown that naive nodes can deteriorate the network performance due to their inaccurate estimation values.

Several distributed Kalman filter schemes were given in Kamal, Song, Farrell, and Roy-Chowdhury (2011); Kamal et al. (2013) and Wang, Ren, and Li (2014) to remedy these issues. In those works, distributed local consensus filters were developed that have information weighting, that is, weighting by the inverse of the estimation error covariance matrix. Simulations showed improved performance relative to that of the KCF (Olfati-Saber, 2007). These works are for the discrete-time case and cannot easily be extended to the continuous-time case.

Another distributed KCF called Multi-agent Kalman consensus filter (MKCF) was given in Ren, Beard, and Kingston (2005), Analogous to process and measurement noises, channel communication noises may also deteriorate the accuracy of estimation. To address this issue, both discrete-time and continuous-time MKCF are studied therein. In that work, the resulting filtering algorithms do not contain the state of the target node, so it is not clear that it is actually being estimated, even though a consensus estimate is reached. Alighanbari and How (2006) proposed a modified version of this algorithm to obtain an unbiased estimation.

The aim of this paper is to develop a novel Information-weighted Kalman Consensus Filter (IKCF), with improved properties, for continuous-time systems. A goal is to provide an optimal distributed consensus filter whose convergence can be formally proven. The approach is to impose the information flow topology up-front by assuming a distributed form for the measurement matrices of the sensor nodes. Then, the Kalman filter equations are formally applied to develop locally optimal distributed consensus filters wherein the effects of poor estimates of neighbors are discounted using information weighting terms.

The contributions of the IKCF in this paper are as follows.

(1) The information flow topology is formally captured up-front in the Kalman filter formulation by defining a distributed information-weighted measurement model for each node. Both process noises and channel communication noises are included.