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Observer-enhanced distributed moving horizon state estimation subject to communication delays

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ABSTRACT

In this work, we focus on distributed moving horizon estimation (DMHE) of nonlinear systems subject to time-varying communication delays. In particular, a class of nonlinear systems composed of subsystems interacting with each other via their states is considered. In the proposed design, an observer-enhanced moving horizon state estimator (MHE) is designed for each subsystem. The distributed MHEs exchange information via a shared communication network. To handle communication delays, an open-loop state predictor is designed for each subsystem to provide predictions of unavailable subsystem states (due to delays). Based on the predictions, an auxiliary nonlinear observer is used to generate a reference subsystem state estimate for each subsystem. The reference subsystem state estimate is used to formulate a confidence region for the actual subsystem state. The MHE of a subsystem is only allowed to optimize its subsystem state estimate within the corresponding confidence region. Under the assumption that there is an upper bound on the time-varying delays, the proposed DMHE is proved to give decreasing and ultimately bounded estimation error. The theoretical results are illustrated via the application to a reactor–separator chemical process.

1. Introduction

The operation of large-scale complex processes for increased efficiency and profits is a challenging task which has attracted significant attention. In recent years, different types of networked control architectures have been developed for the control of large-scale processes. Among these control architectures, one promising approach is distributed model predictive control (DMPC) which becomes very popular due to its ability to deal with scale and interaction issues in large-scale complex processes [1–3]. The existing DMPC algorithms can be broadly classified into non-cooperative and cooperative DMPC algorithms based on the cost function used in the local controller optimization problem [1]. In a non-cooperative DMPC algorithm, each local controller optimizes a local cost function while in a cooperative DMPC algorithm, a local controller optimizes a global cost function. Non-cooperative DMPC algorithms include [4–9]. Cooperative DMPC was first proposed in [10] and was developed in [1,11,12]. Lyapunov-based cooperative DMPC algorithms for nonlinear systems were also developed in [13,14] in recent years. It has been demonstrated that DMPC has the potential to achieve the performance of the centralized control while preserving the flexibility of decentralized frameworks [11,15]. In addition to DMPC, other important work within process control includes the development of a quasi-decentralized control framework for multi-unit plants that achieves the desired closed-loop objectives with minimal cross communication between the plant units under state feedback control [16]. However, almost all of the above results are derived under the assumptions that the system states are available all the times or that a centralized state observer is available. These assumptions, however, either fail in many applications or are inconsistent with the distributed framework which is not favorable from a fault tolerance point of view. Therefore, it is desirable to develop state estimation schemes in the distributed framework.

In the literature, a majority of the existing results on state observer designs are derived in the centralized framework. For linear systems, Kalman filters and Luenberger observers are standard solutions. In the context of nonlinear systems, observer designs including high-gain observers for different specific classes of nonlinear systems are available (e.g., [17–26]). In a recent work [27], observers for systems with delayed measurements were also developed. It is worth noting that the capability of high-gain observers to be used in output feedback

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control designs has made high-gain observers very popular in output feedback control of nonlinear systems (e.g., [28–33]). In another line of work, moving horizon estimation (MHE) has become popular because of its ability to handle explicitly nonlinear systems and constraints on decision variables (e.g., [34–37]). In MHE, the state estimate is determined by solving online an optimization problem that minimizes the sum of squared errors. In order to have a finite dimensional optimization problem, the horizon (estimation window size into the past) of MHE is in general chosen to be finite. At a sampling time, when a new measurement is available, the oldest measurement in the estimation window is discarded, and the finite horizon optimization problem is solved again to get the new estimate of the state [38,34]. In a recent work [39], a robust MHE scheme was developed which effectively integrates deterministic (high-gain) observers into the MHE framework. The resulting robust MHE scheme gives bounded estimation error and has a tunable convergence rate. This makes the robust MHE suitable for output feedback control system design and has been applied in the design of an output feedback Lyapunov-based MPC [40] and an output feedback economic MPC [41].

Within the decentralized/distributed frameworks, there are some results developed in the context of linear systems and a few results for nonlinear systems in the framework of MHE. For linear systems, the results focus on decentralized deterministic observers (e.g., [42–45]) and distributed Kalman filtering methods for sensor networks (e.g, [46–49]). Recently, in the framework of moving horizon estimation, distributed MHE (DMHE) schemes were also developed for constrained linear systems [50,51]. For nonlinear systems, distributed moving horizon estimation schemes (DMHE) were developed with the local MHE designed based on a centralized model [52] or the subsystem model [53]. The above DMHE schemes are based on the classical centralized MHE as in [34] and they inherit the advantages of classical MHE including the capability to handle nonlinearities, constraints and optimality. However, it is not easy to characterize the effects of bounded uncertainties.

In a recent work [54], an observer-enhanced DMHE design was developed for a class of nonlinear systems with bounded process uncertainties. In this DMHE, each subsystem MHE communicates with subsystems that it interacts with every sampling time. In the design of each subsystem MHE, an auxiliary deterministic nonlinear observer is taken advantage of to calculate a confidence region that contains the actual system state every sampling time. The subsystem MHE is only allowed to optimize its state estimate within the confidence region. This strategy was demonstrated to guarantee the convergence and ultimate boundedness properties of the estimation error. However, the above results were derived under the assumption that the communication between subsystems is flawless and there is no delay in the information transmission. In practice, this assumption may not hold especially when shared wireless communication network is used. Issues brought into the design by communication need to be carefully addressed [55].

Motivated by the above considerations, in this work we proposed a DMHE scheme that is able to handle time-varying communication delays. In the proposed design, a nonlinear observer-enhanced MHE is designed for each subsystem and the distributed MHEs are assumed to be able to communicate and exchange information with each other via a shared communication network which may introduce communication delays. To handle time-varying delays in the communication, an open-loop state predictor is designed for each subsystem to provide predictions of unavailable subsystem states. In the design of each predictor, the centralized system model is used. Based on the state predictions, an auxiliary nonlinear observer is used to generate a reference subsystem state estimate for each subsystem every sampling time. Based on the reference subsystem state estimate as well as the local output measurement, a confidence region is constructed for the actual state of a subsystem. A subsystem MHE is only allowed to optimize its state estimate within the corresponding confidence region at a sampling time. The proposed DMHE is proved to give decreasing and ultimately bounded estimation errors under the assumption that there is an upper bound on the time-varying delay. The theoretical results are illustrated via the application to a reactor–separator chemical process, and the proposed approach is shown to be superior to a DMHE approach without considering communication delays explicitly.

Notation. The operator $|\cdot|$ denotes Euclidean norm of a scalar or a vector while $|\cdot|_Q$ indicates the weighted Euclidean norm of a vector, defined as $|x|_Q = \sqrt{x^T Q x}$ where Q is a positive definite square matrix. A function $f(x)$ is said to be locally Lipschitz with respect to its argument x if there exists a positive constant L_f^x such that $|f(x') - f(x'')| \le L_f^x |x' - x''|$ for all x' and x'' in a given region of x and L_f^x is the associated Lipschitz constant. A continuous function $\alpha : [0, a) \to [0, \infty)$ is said to belong to class $\mathcal{K}$ if it is strictly increasing and satisfies $\alpha(0) = 0$. A function $\beta(r, s)$ is said to be a class $\mathcal{KL}$ function if for each fixed s, $\beta(r, s)$ belongs to class $\mathcal{K}$ with respect to r, and for each fixed r, it is deceasing with respect to s, and $\beta(r, s) \to 0$ as $s \to \infty$. The symbol diag(v) denotes a diagonal matrix whose diagonal elements are the elements of vector v. A matrix (or vector) A^+ denotes the pseudoinverse of a matrix (or vector) A. The symbol '\' denotes the set subsection such that $\mathbb{A} \backslash \mathbb{B} := \{x \in \mathbb{R}^{n_x} | x \in \mathbb{A}, x \notin \mathbb{B}\}$. The set $\mathbb{I} = \{1, \ldots, m\}$.

2. Preliminaries

2.1. Problem formulation

In this work, we consider a class of nonlinear systems composed of m interconnected subsystems, which are described by the following state-space model:

$$\begin{aligned} \dot{x}_i(t) &= f_i(x_i(t), w_i(t)) + \tilde{f}_i(X_i(t)) \\ y_i(t) &= h_i(x_i(t)) + v_i(t) \end{aligned} \tag{1}$$

where $x_i(t) \in \mathbb{R}^{n_{x_i}}$, $i \in \mathbb{I}$, is the state vectors of subsystem i, $w_i(t) \in \mathbb{R}^{n_{w_i}}$ characterizes disturbances associated with subsystem i, and the vector function f_i denotes the dependence of the dynamics of x_i on itself and the associated disturbances. The vector function $\tilde{f}_i$ denotes the interactions between subsystem i and other subsystems. The vector $y_i \in \mathbb{R}^{n_{y_i}}$ is the measured output of subsystem i and $v_i \in \mathbb{R}^{n_{v_i}}$ is a measurement noise vector. We assume that the system disturbances and measurement noise are bounded: $w_i \in \mathbb{W}_i$ and $v_i \in \mathbb{V}_i$ where $\mathbb{W}_i := \{w_i \in \mathbb{R}^{n_{w_i}} : |w_i| \le \theta_{w_i}\}$, $\mathbb{V}_i := \{v_i \in \mathbb{R}^{n_{v_i}} : |v_i| \le \theta_{v_i}\}$, with θ_{w_i} and θ_{v_i}, $i \in \mathbb{I}$, known positive real numbers. We further assume that f_i, $\tilde{f}_i$, and h_i for all $i \in \mathbb{I}$ are locally Lipschitz.

The state vector $X_i(t)$ contains subsystem states involved in the interaction term of subsystem i with other subsystems. In this work, $\mathbb{I}_i \subset \mathbb{I}$ $(i \in \mathbb{I})$ will be used to denote the set of subsystem indices whose corresponding subsystem states are involved in X_i. It should be noted that x_i may be involved in X_i. In this work the sets $\mathbb{I}_i$ $(i \in \mathbb{I})$, are assumed to be known and will be used in the description of the proposed