Systems & Control Letters 75 (2015) 56–68

Contents lists available at ScienceDirect

Systems & Control Letters

journal homepage: www.elsevier.com/locate/sysconle

Distributed moving horizon state estimation: Simultaneously handling communication delays and data losses[☆]

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ARTICLE INFO

Article history:
Received 17 July 2014
Received in revised form
6 November 2014
Accepted 10 November 2014
Available online 4 December 2014

Keywords:
Nonlinear systems
Distributed state estimation
Moving horizon estimation
Communication algorithms
Chemical processes

ABSTRACT

In this work, we consider distributed moving horizon state estimation of nonlinear systems subject to communication delays and data losses. In the proposed design, a local estimator is designed for each subsystem and the distributed estimators communicate to collaborate. To handle the delays and data losses simultaneously, a predictor is designed for each subsystem estimator. A two-step prediction-update strategy is used in the predictor design in order to get a reliable prediction of the system state. In the design of each subsystem estimator, an auxiliary nonlinear observer is also taken advantage of to calculate a reference subsystem state estimate. In the local estimator, the reference state estimate is used to generate a confidence region within which the local estimator optimizes its subsystem state estimate. Sufficient conditions under which the proposed design gives decreasing and ultimately bounded estimation error are provided. The effectiveness of the proposed approach is illustrated via the application to a chemical process example.

1. Introduction

In recent years, there is significant attention on the development of distributed predictive control schemes for plant-wide control of large-scale complex chemical processes [1–3]. In these distributed schemes, different controllers communicate with each other to coordinate their actions to achieve improved control performance over decentralized control schemes; see, for example, [4–11]. It has been demonstrated that these distributed schemes are particularly useful for large-scale integrated process networks [12,13] such that the coupling between different operating units cannot be neglected. However, almost all of these distributed predictive control schemes are dependent on the availability of the state measurements of the entire system. It is desirable to develop state estimation schemes in the distributed framework.

In the literature, the results on decentralized or distributed state estimation are basically within three frameworks: decentralized deterministic observers, distributed Kalman filtering and distributed moving horizon estimation. Decentralized deterministic observers have been developed for different classes of system but primarily in the context of linear systems (e.g., [14–17]). Significant efforts have been devoted to the development of distributed Kalman filtering methods for sensor networks also primarily in the context of linear systems (e.g., [18–20]). Distributed moving horizon estimation (DMHE) schemes were developed for both linear constrained systems [21,22] and nonlinear systems [23]. The above DMHE schemes have their origins from classical centralized moving horizon estimation (MHE) [24]. They have the appealing features of dealing with nonlinearities, constraints and optimality. However, it is not easy to characterize the effects of bounded uncertainties which is important from the output feedback control point of view.

To address the above issues, an observer-enhanced DMHE design to estimate the state of large-scale systems in a distributed manner was developed in [25]. The DMHE design in [25] is based on a robust MHE developed in [26] where an auxiliary deterministic observer is taken advantage of to calculate confidence regions for the actual system state and the local MHEs are only allowed to optimize their subsystem state estimates within the regions. It has been shown that the DMHE scheme gives ensured ultimate boundedness properties of the estimation error. Since in a distributed framework, communication between different controllers/estimators is critical, it is of great importance to carefully

☆ Financial support from the Natural Science Foundation of Liaoning Province, China (2014020138), the Program for Liaoning Province Distinguished Young Scholars in University (LJQ2014045) and the University of Alberta (RES0014908) is acknowledged.

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http://dx.doi.org/10.1016/j.sysconle.2014.11.007
0167-6911/

consider issues that may be brought into the design by (especially wireless) communication [27,28]. In [29], an approach was developed to handle time-varying delays in the communication network of DMHE schemes. One limitation of the approach in [29] is that it requires that all the transmitted information should be received within a maximum allowable number of sampling periods. The approach in [29] is not capable of handling data losses in the shared communication network which is one of the key issues introduced by communication.

Inspired by the above considerations, in this work, we focus on the development of a distributed moving horizon estimation scheme that is capable of handling communication delays and data losses simultaneously. In the proposed design, a local MHE is designed for each subsystem and the distributed local MHEs communicate to exchange information and collaborate. In the communication network, there may be time-varying delays and data losses. To handle the delays and data losses simultaneously, a predictor is designed for each subsystem estimator. A two-step prediction-update strategy is used in the predictor design in order to get a reliable prediction of the system state. Based on the predictions as well as output measurements, an auxiliary nonlinear observer is taken advantage of in each subsystem estimator to generate a reference subsystem state estimate. In the local MHE design, the reference state estimate is used to generate a confidence region within which the local MHE optimizes its subsystem state estimate. Sufficient conditions under which the proposed DMHE gives decreasing and ultimately bounded estimation error are provided. Extensive simulations based on a chemical process example illustrate the effectiveness of the proposed approach by comparing it with three different distributed state estimation schemes from different aspects.

Notation. The operator $|\cdot|$ denotes Euclidean norm of a scalar/vector while $|\cdot|_Q$ indicates the weighted Euclidean norm of a vector, defined as $|x|_Q = \sqrt{x^TQx}$ where Q is a positive definite symmetric 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 $|f(x_a) - f(x_b)| \le L_f^x|x_a - x_b|$ for all x_a and x_b 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 decreasing 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. System description and problem formulation

We consider nonlinear systems that are composed of m interconnected subsystem. In particular, we consider that the dynamics of subsystem i can be described as follows:

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

where $x_i(t) \in \mathbb{R}^{n_{x_i}}$ and $y_i(t) \in \mathbb{R}^{n_{y_i}}$ denote the state vector and output vector of subsystem i, respectively, $w_i(t) \in \mathbb{R}^{n_{w_i}}$ and $v_i(t) \in \mathbb{R}^{n_{v_i}}$ characterize disturbances and measurement noise of subsystem i, respectively. The term $\tilde{f}_i(X_i)$ characterizes the interaction of subsystem i with other subsystems and X_i contains subsystem states involved in characterizing the interaction. The set $\mathbb{I}_i \subset \mathbb{I}$ ($i \in \mathbb{I}$) will be used to denote the set of subsystem indices such that the corresponding subsystem states are involved in X_i. It is assumed that the subsystem states x_i, $i \in \mathbb{I}$, are contained in convex complex sets such that $x_i \in \mathbb{X}_i$, $i \in \mathbb{I}$.

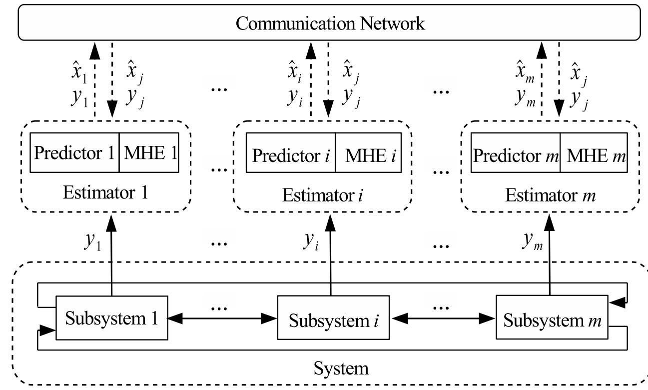

Fig. 1. The proposed DMHE design with communication delays and data losses.

It is assumed that the subsystem disturbances and measurement noise are bounded such as $w_i \in \mathbb{W}_i$ and $v_i \in \mathbb{V}_i$ for all $i \in \mathbb{I}$ where $\mathbb{W}_i := \{w_i \in \mathbb{R}^{n_{w_i}} : |w_i| \le \theta_{w_i}\}$ and $\mathbb{V}_i := \{v_i \in \mathbb{R}^{n_{v_i}} : |v_i| \le \theta_{v_i}\}$ with $\theta_{w_i}, \theta_{v_i}$ for $i \in \mathbb{I}$ known positive real numbers. It is also assumed that $f_i, \tilde{f}_i$ and h_i with $i \in \mathbb{I}$ are locally Lipschitz.

The entire system state x and output y are aggregations of the subsystem states and outputs respectively such that $x = [x_1^T \cdots x_i^T \cdots x_m^T]^T \in \mathbb{R}^{n_x}$ and $y = [y_1^T \cdots y_i^T \cdots y_m^T]^T \in \mathbb{R}^{n_y}$. The dynamics of the entire nonlinear system can be written in a compact form as follows:

$$\begin{aligned} \dot{x}(t) &= f(x(t), w(t)) + \tilde{f}(x(t)) \\ y(t) &= h(x(t)) + v(t) \end{aligned} \tag{2}$$

where $w(t) \in \mathbb{R}^{n_w}$ is disturbance vector and $v(t) \in \mathbb{R}^{n_v}$ is the measurement noise vector which are aggregations of the subsystem disturbance vectors and noise vectors, respectively, and $f, \tilde{f}$ and h are aggregations of $f_i, \tilde{f}_i$ and h_i for all the subsystems, respectively. It is assumed that the outputs of the m subsystems are sampled synchronously and periodically at time instants $\{t_{k\ge0}\}$ such that $t_k = t_0 + k\Delta$ where $t_0 = 0$ is the initial time, Δ is a fixed sampling time interval and k is a positive integer.

The objective of this work is to design a DMHE scheme for system (2) that is capable of handling both communication delays and data losses between local MHEs. A schematic of the proposed design is shown in Fig. 1. In this design, each subsystem is associated with a local state estimator which includes a state predictor and a moving horizon state estimator. The subsystem estimators communicate with each other via a shared communication network to exchange information. The information exchanged via the shared communication network may be subject to time-varying delays or data losses.

In [29], an approach was developed to handle communication time-varying delays in the communication network of DMHE schemes. The approach requires that all the transmitted information should be received within a maximum allowable number of sampling periods (i.e., the maximum allowable delay). However, the approach is not capable of systematically handling data losses in the shared communication network. In this work, we propose a more general and unified approach to handle both communication data losses as well as delays.

2.2. Observability assumptions and nonlinear observers

The local MHEs will be designed in the framework of robust MHE [26]. An auxiliary nonlinear observer will be taken advantage of in the design of each local MHE to calculate a reference state