Computers and Chemical Engineering 80 (2015) 63–72

Contents lists available at ScienceDirect

Computers and Chemical Engineering

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

Application of MHE to large-scale nonlinear processes with delayed lab measurements☆

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ARTICLE INFO

Article history:
Received 14 November 2014
Received in revised form 12 April 2015
Accepted 15 April 2015
Available online 8 May 2015

Keywords:
Moving horizon estimation
Nonlinear state estimation
Multi-rate sampling measurements
Observability
Polymer process

ABSTRACT

The paper addresses nonlinear estimation problems on nonlinear processes containing several lab measurements sampled slowly and with long delay, which is the usual case in industrial polymerization applications. A moving horizon estimation algorithm is developed to compute the theoretical optimal solution given the multi-rate measurements. In this algorithm, the MHE window is recalculated as the new lab measurement becomes available. Simulation studies on a polymerization process with plant model mismatch are performed. Observability analysis and estimation results of MHE with and without lab measurements show that lab measurements help identify the disturbances and can improve the performance of both estimation and closed-loop control.

1. Introduction

Advanced feedback control for nonlinear systems such as model predictive control (MPC) includes a state estimator which uses the past inputs and measurements to provide the best estimate of the current state of the system. The control inputs are then determined by the regulator based on the state estimate and the model. Thus, the performance of closed-loop MPC is directly affected by the quality of the state estimates. The states of many chemical processes are complex product properties and are not directly measurable from sensors. Also, these processes are characterized by both nonlinearity in the dynamics and significant levels of process and sensor noise. To solve the nonlinear state estimation problem, a natural starting point is Bayesian estimation, which maximizes the conditional probability of all state sequence given all available measurements. For the application purpose, Bayesian estimation is specified as the optimization-based methods including full information estimation (Rawlings and Bakshi, 2006) and moving horizon estimation (MHE) (Alessandri et al., 2008; Rao and Rawlings, 2002; Rao et al., 2003; Robertson and Lee, 2002; Robertson et al., 1996). MHE truncates the objective by a fixed horizon and therefore avoids an increasing computational burden. MHE is usually slower than one-step filter-based methods such as extended Kalman filter (EKF) (Jazwinski, 1970; Bryson and Ho, 1975) but often shows better stability, accuracy and convergence to the true state (Haseltine and Rawlings, 2005).

A significant industrial challenge for nonlinear state estimation is that the different measurements may not be sampled at the same rate. The system may contain fast measurements such as temperature and pressure, which can be sampled online and be available immediately, and slow measurements such as melt index, density, and viscosity, which are sampled infrequently and usually have measurement delays. Polymerization processes are typically characterized by multi-rate sampling measurements, since the polymer properties are usually measured by lab analysis instead of automatic sensors. Different estimation technologies on systems with multi-rate sampling measurements have been proposed. As a rough approximation, the missing data of slow measurements can be predicted by polynomial extrapolation such that the nominal estimation method can be applied (Tatiraju et al., 1999; Zambare et al., 2003). If a deterministic observer is available, it can also be adjusted to handle multi-rate measurements (Zambare et al., 2002). Most efforts on the estimation with multi-rate sampling measurements are Extended Kalman Filter (EKF)-based, including parallel filters (Larsen et al., 1998), fixed-lag smoothing (Gudi et al., 1994; Mutha et al., 1997) which augments the states to cover the measurement delay, and filter recalculation starting from the time the slow measurement was taken (Prasad et al., 2002). Gopalakrishnan et al.

☆ This work was supported by the industrial members of the Texas Wisconsin California Control Consortium (TWCCC).
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http://dx.doi.org/10.1016/j.compchemeng.2015.04.015
0098-1354/

(2011) compare the different methods and extends these methods to the case of time-varying and uncertain delays. MHE studies on system with multi-rate measurements have also been developed. Krämer et al. propose two MHE studies (Krämer et al., 2005; Krämer and Gesthuisen, 2005) using either a fixed or a variable structure. The former assumes a zero order hold on the last available measurement and the latter uses only the slow measurements in the sample times when they are available (Krämer and Gesthuisen, 2005). López-Negrete and Biegler (2012) also apply a variable structure of MHE by setting the MHE horizon large enough to cover both the sampling time and the arrival time of slow measurements.

Here we have particular interest in industrial online implementation of MHE on large-scale polymerization processes, in which the polymer properties are usually measured in the lab, characterized by long sampling interval and long time delays. In this case, the method proposed in López-Negrete and Biegler (2012) becomes impractical because the size of the MHE problem would become too large. Both the large dimension of the state and the large horizon to cover the measurement delay increase the size of the MHE problem. Although this issue can be fixed by manually slowing down the sampling of the fast measurements, in this paper we propose a method using the original sampling rates of the measurements. We overcome the obstacles by combining the idea of estimator recalculation with the general MHE formulation. Upon the arrival of some lab measurement, MHE performs the recalculation starting from its sampling time. This method yields the solution of the Bayesian estimation on processes with multi-rate sampling measurements. The method also works for the case with irregular sampling intervals or measurement delays. Due to the computational burden required for the recalculation step, we demonstrate situations in which utilizing delayed lab data is worthwhile. Lab measurements should be used when some states are unobservable using only the fast measurements, but these states become observable when lab measurements are included (Mutha et al., 1997; Tatiraju et al., 1999; Zambare et al., 2002). Lab measurements may help improve the transient behavior of the estimator by recovering quickly from an inaccurate prior (Tatiraju et al., 1999; López-Negrete and Biegler, 2012). As a second more complicated case study, we investigate when the lab measurements help identify the plant model mismatch and help the estimator converge to the true state (Mutha et al., 1997).

In this paper, we first derive the algorithm for recalculated MHE with delayed lab measurements, starting from the objective of Bayesian estimation. The derivation is similar to previous results (Rawlings and Bakshi, 2006) but here the structure of measurement functions becoming time-varying. A gas-phase ethylene copolymerization process model from the literature (McAuley et al., 1990; Dadebo et al., 1997; Gani et al., 2007) is then studied. See also Ramlal et al. (2007) for state estimation and control of a gas-phase polymerization process without lab measurements. Challenges of estimation on this process include weak observability, large state dimension, and strong nonlinearity. The process also contains two important polymer properties, melt index and polymer density, which are critical indicators of polymer grades (McAuley and MacGregor, 1992) and usually used as the control targets (McAuley and MacGregor, 1993). In a previous study, we assumed these properties were also fast measurements (Lima et al., 2013). To be more realistic, here we assume they are measured in a lab and subject to long sampling intervals and time delays. We perform a quantitative observability analysis that verifies that the inclusion of lab measurements could improve the observability of the global system and some critical states. These conclusions were reached only qualitatively in Mutha et al. (1997). Estimation of the process with delayed lab measurements shows improved accuracy when subject to an unmodeled deterministic disturbance. Finally, a closed-loop case study shows the impact of improved estimation on the closed-loop control performance. The MHE implementation is fast enough for online implementation including the recalculation steps.

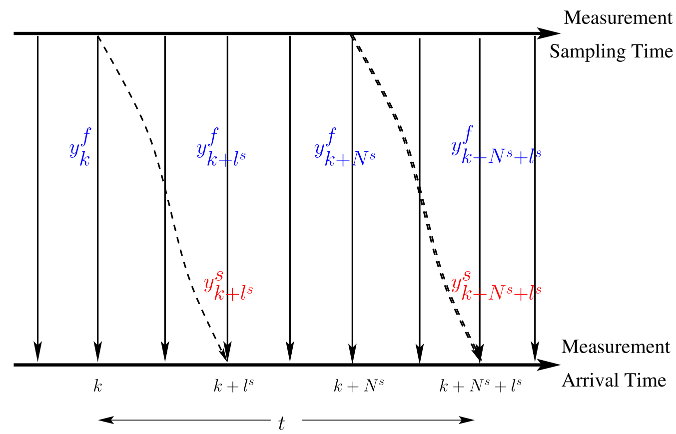

Fig. 1. An example system with multi-sampling rate measurements. The slow measurements are sampled once per N^s steps and delayed by l^s steps.

The paper is organized as follows. For the paper to be reasonably self contained, we provide a brief introduction of the nonlinear system and multi-rate sampling measurements. We then formulate the MHE algorithm on this class of systems and show that it is equivalent to Bayesian estimation. Then we provide the main application of the paper: a case study of MHE on a polymerization process with incorporation of lab measurements. The impact of lab measurements on system observability, estimation accuracies and closed-loop control performance are presented. We also discuss weaknesses of the approach and future directions of current multi-rate measurement algorithms.

2. System with multi-rate sampling measurements

The discrete time, nonlinear system with multi-sampling rate measurements is defined as

$$
\begin{aligned}
x_{k+1} &= F(x_k) + w_k \\
y^f_k &= h^f(x_k) + v^f_k \\
y^s_{k+l^s} &= h^s(x_k) + v^s_k, \quad k \in \mathbb{K}^s
\end{aligned} \tag{1}
$$

in which $x \in \mathbb{R}^n$ is the state, $y^f \in \mathbb{R}^{p^f}$ is the fast measurement, and $y^s \in \mathbb{R}^{p^s}$ is the slow measurement. $\mathbb{K}^s$ is the set of k when the slow measurements are sampled, *e.g.*, when the slow sampling interval is regular and denoted as N^s, then $\mathbb{K}^s = \{k | k = iN^s, i = 0, 1, \ldots\}$; l^s is the measurement delay. Fig. 1 shows a schematic representation of multi-rate sampled measurements.[1] The manipulated input $u \in \mathbb{R}^m$ may also be included in the model; since it is considered a known variable and its inclusion is irrelevant to the state estimation topic, we suppress it in the model under consideration here. The process is corrupted by the process noise w and the measurement noises v^f and v^s, which are modeled as independent zero-mean Gaussian variables

$$
w \sim \mathcal{N}(0, Q_w), \quad v^f \sim \mathcal{N}(0, R^f_v), \quad v^s \sim \mathcal{N}(0, R^s_v) \tag{2}
$$

Prior information of the initial state is also assumed to be known as $x_0 \sim \mathcal{N}(\bar{x}_0, P_0)$.

[1] Here N^s and l^s are constant for clearer illustration; but notice that our method also work for the case when N^s and l^s are variant with $\mathbb{K}^s$ defined accordingly.