Journal of Process Control 69 (2018) 158–178

Contents lists available at ScienceDirect

Journal of Process Control

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

Development of robust extended Kalman filter and moving window estimator for simultaneous state and parameter/disturbance estimation

Jayaram Valluru [a], Sachin C. Patwardhan [a,*], Lorenz T. Biegler [b]

[a] Department of Chemical Engineering, Indian Institute of Technology Bombay, Mumbai 400076, India
[b] Department of Chemical Engineering, Carnegie Mellon University, Pittsburgh, PA 15213, USA

ARTICLE INFO

Article history:
Received 6 October 2017
Received in revised form 24 May 2018
Accepted 25 May 2018

Keywords:
Measurement gross errors
Robust estimation
M-estimators
Simultaneous state and parameter estimation
Extended Kalman filter
Moving window estimator

ABSTRACT

Simultaneous occurrence of gross errors (outliers/biases/drifts) in the measured signals, and drifting disturbances/parameter variations affecting the system dynamics can lead to biased state estimates, and, in turn, can lead to deterioration in the performance of model-based monitoring and control schemes. In this work, robust recursive and moving window based Bayesian state and parameter estimators are developed that are robust w.r.t. gross errors in the measurements and can simultaneously estimate non-additive unmeasured disturbance/parameter variations. Using Bayes' rule, the update step of Kalman filter (KF) is recast as an optimization problem. The optimization is then modified by replacing the likelihood term in the objective function with cost function defined by an M-estimator. The M-estimators considered in this work are Huber's Fair function and Hampel's redescending estimator. The reformulated KF is then used as a basis for reformulating extended Kalman filter (EKF). This re-formulated EKF is then used for developing robust simultaneous state and parameter estimation schemes. In particular, a robust version of recently proposed moving window based state and parameter estimator [1] has been developed. The resulting formulation can be viewed as a hybrid approach, in which the gross errors in the measurements are dealt with in a passive manner, with an active elimination of model plant mismatch by estimating unmeasured disturbance/parameter variations simultaneously. The efficacy of the proposed robust state and parameter estimators is demonstrated by conducting simulation studies and experimental studies. Analysis of the simulation and experimental results reveal that the proposed robust recursive and moving window based state and parameter estimators significantly reduce or completely nullify the effect of gross errors on the state estimates while simultaneously estimating drifting unmeasured disturbances/parameters. The simulation study also underscores the importance of simultaneous estimation of unmeasured disturbances/parameters while achieving robustness using the M-estimators. Moreover, Hampel's redescending estimator is found to be a better choice of M-estimator than the popular Huber's Fair function, as the redescending estimator can completely nullify the effect of gross errors on the state and parameter estimates.

1. Introduction

Accurate information of states and parameters/disturbances is essential for effective monitoring, control and real-time optimization of any system. For chemical processes, in particular, the majority of the system state variables are not available as measurements. Only a few of the state variables such as selected temperatures, levels, and pressures can be frequently measured. On the other hand, the product quality related variables such as compositions in a reactor, molecular weight distribution in a polymer reactor, biomass in fermentor, etc., are difficult to measure and have to be inferred from the available online data and the models relating the measurements with the quality variables. Further, the model parameters, such as heat transfer coefficients, reaction rate constants, and, unmeasured disturbances, such as feed compositions, may slowly drift from their nominal values over a period of time. Thus, to operate a plant in an optimal manner, it becomes necessary to track the changing parameters/unmeasured disturbances and use them for improving performances of monitoring, control and real-time optimization schemes.

* Corresponding author.
E-mail address: sachinp@iitb.ac.in (S.C. Patwardhan).

https://doi.org/10.1016/j.jprocont.2018.05.008
0959-1524/

The accuracy of the inferred states and parameters critically depend on the accuracy of the measurement data. In practice, the process measurements are typically corrupted with *random errors* and infrequently occurring *gross errors*. Random errors correspond to the noise in the sensors and are typically zero mean, while the gross errors are non-zero mean signals [2]. Gross errors in the measurements arise because of miscalibration of sensors, failure of sensors and drift in the sensor measurements due to fouling of the sensors, etc. [3]. The three classical types of gross errors that occur in the operating plants are outliers, biases, and drifts. Outliers occur due to change in power supply/fluctuations, signal conversion, and faults that result in a sudden spike. Bias is caused by incorrect calibration or malfunction of a sensor. Drifts are caused by wear or fouling of sensors and occur gradually over a period of time [4–6]. These gross errors introduce inaccurate information in the measurements. The measurements corrupted with the gross errors have a significant impact on the quality of estimated states and parameters, thereby deteriorating the performance of monitoring, control and real-time optimization schemes. Thus, to obtain accurate estimates of states and parameters in the presence of gross errors, the effect of measurements corrupted with gross errors on the state/parameter estimates has to be minimized or completely eliminated.

While developing any dynamic model-based Bayesian state estimation technique, such as the Kalman filter and its extensions to nonlinear filtering or moving horizon estimator (MHE), it is assumed that the measurements are corrupted only with the random errors and measurement noise is a zero-mean white noise process [7]. In the presence of gross errors in the measurements, the measurement noise is no longer a stationary zero mean signal and the exact noise distribution is difficult to determine [3]. Further, direct use of such corrupted measurements in the estimation leads to biases in the estimated states and parameters. Thus, the focus of the current work is to develop simultaneous state and parameter estimation approaches that are robust or insensitive to the gross error in the measurements.

Achieving robustness with respect to gross errors in measurements and in state dynamics has been an active area of research. The approaches available in the literature can be broadly classified as active and passive approaches. The active approaches try to isolate the root cause of the gross error, estimate the gross error magnitude(s) and actively compensate for the gross errors while carrying out state estimation [8–13]. This approach involves a series of tests i.e. detection, isolation, magnitude estimation and compensation for bias; it involves more computing. Thus, carrying out online gross error detection and diagnosis using an active approach for larger dimensional systems is a difficult task. The passive approaches, on the other hand, attempt to make the state estimates insensitive to gross errors in measurements and/or state dynamics [3,6,14–19] and can be used relatively easily to deal with moderately large dimensional systems.

Developing robust Kalman filters (KF) has been a major focus of much of the literature that employs passive approaches. In fact, the literature on robust KF treats gross errors in the measurements as well as in the state dynamics (e.g.: non-zero mean additive drifting unmeasured disturbances influencing the state dynamics). A passive approach that has gained importance over the recent years proposes to reduce/eliminate the effect of gross errors by integrating with Maximum likelihood type estimators (or M-estimators) with the Kalman filter. These estimators simultaneously detect and reduce the effect of gross errors on the state and parameter estimates. Moreover, these M-estimators are independent of the state error/measurement distributions and are also insensitive to the deviation from the ideal distributions [20]. The common approach that has been followed in the literature is to recast the Kalman filter as a linear weighted regression problem and then replace the objective function using Huber's M-estimator [14–16]. This approach initially transforms the state estimation and measurement errors (using square roots of their respective covariance matrices) in such a way that the prediction and update steps in the conventional KF calculations can be combined and reduced to a single ordinary least squares problem. The transformed objective function is then replaced by Huber's M-estimators. This approach simultaneously eliminates the gross errors in the state dynamics and the gross errors in the measurements. Alternatively, a H_∞ based KF formulation has been developed that minimizes the worst-case estimation error averaged over all samples [21]. This approach treats modeling errors and uncertainties as unknown but bounded noise. Recently, Gandhi and Mili [22] have developed a robust KF based on a generalized M-estimator to account for measurement, innovation, and structural outliers.

While the majority of the available literature deals with linear systems, some researchers have extended the Huber M-estimator based KF formulation to incorporate robustness in nonlinear state estimators. Karlgaard [23] has developed a robust EKF formulation, which can be viewed as a direct extension of robust KF developed by Boncelet [14]. On similar lines, Wang et al. [24] have developed a robust UKF formulation. Similar to Boncelet [14], both of these formulations make use of transformed state estimation and measurement errors to reformulate the estimation problem. Subsequently, the reformulated problem is modified using Huber's M-estimator. It may be noted that these extensions consider only robustness w.r.t. additive non-stationary disturbances/gross errors influencing the state dynamics. In practice, however, when the system dynamics are nonlinear, the effect of drifting parameters /unmeasured disturbances on the state dynamics is not additive. Robustness w.r.t. both drifting parameters/unmeasured disturbances and gross errors in the measurements is of paramount importance for accurate estimation of states and parameters. Recently, Chang et al. [25] have developed a version of UKF that is robust with respect to only gross errors in the measurements. The covariance of innovation signal is used to transform the innovations, which are then used to construct Huber's M-estimator. However, an attempt to achieve robustness only w.r.t. the gross errors in the measurements, by neglecting the effects of unmeasured disturbances/parameter variations on the state dynamics, can lead to biased state estimates (ref. Section 5.1). Also, working with the transformed innovations instead of the transformed measurement errors may lead to a 'smearing' effect on the estimated states.

In the parallel development, attempts have been made to incorporate robustness in the moving horizon based state estimators w.r.t. gross errors in the measurements [3,6,17–19]. The initial approach was to use contaminated error distributions, where the objective function allows for both random and gross error structures, each with a certain amount of probability [3]. The disadvantage of this approach is that the distribution of the gross errors should be characterized well in advance. Also, the estimates are sensitive to the contaminated normal distribution. The other approach is to use Huber's M-estimators in place of the likelihood term in the cost function. The likelihood term in the objective function can be easily replaced with an M-estimator, and the resulting formulation generates results comparable to an active approach without any iterative or sequential computations [19]. Further, the residuals obtained are unbiased and can be used for gross error detection and identification. M-estimators such as Huber's Fair function, Cauchy function, Lorentzian function, Hampel's redescending estimator and logistic function, have been used for achieving robustness w.r.t. gross errors in measurements [3,17,19,26]. Nicholson et al. [18] developed a robust moving horizon estimator (MHE) by integrating the M-estimators in the MHE objective function, where the approach is demonstrated for estima-